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Table of Contents

The Special Issue table of contents begins on the next page.

Special Issue: Emerging Technologies and Innovation for Digital Economy and Transformation

Digital Transformation: A Global Imperative

Technology Acceptance and Adoption

IoT Technologies

Natural Language Processing for Marketing Research

AI for Marketing Strategies and Customer Social Media Data Analytics

Digital Finance

Editorial Team

The *Journal* is published by the Telecommunications Association (TelSoc), a not-for-profit society registered as an incorporated association. It is the Australian telecommunication industry's oldest learned society. The *Journal* has been published (with various titles) since 1935.

Editorial

A Special Issue

Leith H. Campbell
Managing Editor

Abstract: This editorial introduces the March issue, which includes a main Special Issue section on Emerging Technologies and Innovation for Digital Economy and Transformation, as well as papers from the general submissions. The popular reprint from the *Telecommunication Journal of Australia* is back.

Keywords: Editorial

Special Issue: Emerging Technologies and Innovation for Digital Economy and Transformation

This number of the *Journal* features a Special Issue on Emerging Technologies and Innovation for Digital Economy and Transformation. Digital transformation is happening in most industries worldwide. This Special Issue provides a panoramic view of digital transformation, including its acceptance and the barriers to implementation, in many countries.

The Call for Papers elicited 65 submissions, demonstrating the widespread interest in this topic. Eventually, 23 papers have been selected for publication, an acceptance rate of 35%. The five Guest Editors, Rim Jallouli, Meriam Belkhir, Mohamed Anis Bach Tobji, Beatriz Casais and Ana Maria Soares, worked diligently to organize peer reviews and to identify the papers to be published. I would like to thank them for their sustained efforts over many months and to recognize especially the leadership of Professor Jallouli in bringing the Special Issue together. The Guest Editorial (Jallouli *et al.*, 2024) provides some context for the Special Issue and an overview of the content.

Elsewhere in This Issue

We also publish a variety of papers in our usual sections. We have a Special Interest paper, *Growing Australia's Creative Industry*, which follows a presentation to TelSoc and describes the report on this topic by the Australian Broadband Advisory Council in March 2022.

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In the Telecommunications section, we have three papers. *Fusion-Based 2.5D Face Recognition System* continues our recent interest in automated recognition systems. *A Systematic Literature Review on the Role of Big Data in IoT Security* looks at the topic of security in the Internet of Things. *Incidents and Impacts on Operator Revenue in the Telecommunications Sector* analyses data from Ghana on the effects of telecommunications outages and faults.

We also have a Book Review of a recent book on *Charles Todd and the Overland Telegraph Line*.

In the History of Telecommunications section, we describe and republish a paper from the *Telecommunication Journal of Australia* in 1971 on *The Australian East-West Radio Relay System*. The projected republication of this paper triggered a companion piece, *The East-West Microwave Radio Relay System – Recollections*, included in this issue, by an engineer who worked on the East-West link and its early upgrades.

As always, we encourage you to consider submitting articles to the *Journal* and we welcome comments and suggestions on which topics or special issues would be of interest. Feedback on the current Special Issue and future issues would be welcome.

Reference

Jallouli, R., Bach Tobji, M. A., Soares, A. M., Casais, B., & Belkhir, M. (2024). Editorial: Emerging Technologies and Innovation for Digital Economy and Transformation. *Journal of Telecommunications and the Digital Economy*, *12*(1), 113–123. https://doi.org/10.18080/jtde.v12n1.945

Growing Australia's Creative Industry

The Australian Broadband Advisory Council Creative Industry Expert Working Group Position Paper

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Co-Founder of Animal Logic and CEO, Animal Logic Entertainment

Abstract: The Australian Broadband Advisory Council (ABAC) released a position paper on the future of Creative Industry in March 2022, as part of series of papers formed by various industry expert working groups. The purpose of the Creative Industry position paper was to provide advice and recommendations to the Minister for Communications on ways to maximise the benefits of the National Broadband Network (NBN) and other high-speed networks in key sectors of the economy. This article outlines the key findings of the position paper and discusses briefly other key global and local activities since the publication of the position paper that are of note, such as Covid-19, the 2023 writers' strike and the concerns around AI technology deployment in the Creative Industry.

Keywords: Creative Industry, Entertainment, Streaming, Immersion.

Introduction

The Australian Broadband Advisory Council ("ABAC"), chaired by Ms Deena Shiff, was set up to advise "the Australian Government on how broadband infrastructure can be leveraged to accelerate economic and social benefits for Australia" (ABAC, 2022, p. 3). ABAC chose the Creative Industry as one area in which to explore the impact that broadband infrastructure has. This decision was made in response to the significant growth of the industry through streaming and immersive content. A position paper on the Creative Industry was prepared by

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ABAC members, Zareh Nalbandian and Vince Pizzica (co-authors of this journal paper), was endorsed by the Creative Industry Expert Working Group, and was released in March 2022.

This article discusses the findings made in that position paper and beyond its publication, touching on the further technological impacts being felt by the industry. The current widespread deployment of accessible Artificial Intelligence (AI) technologies within creative industry and processes validates now more than ever how digital infrastructure is critical to the global positioning in this sector, while also offering a wider range of commercial opportunities than ever before.

The Creative Industry

The Creative Industry sector encompasses many different mediums, including entertainment content. Content can be delivered by several methods, from live performance, to traditional television on free-to-air channels, and to online streaming and on-demand services. The most common (and therefore most emphasised in the report) are those streamed and traditionally delivered.

Entertainment content broadly includes, but is not limited to, games, film, television, advertising and marketing, interactive (augmented/virtual reality), and location-based entertainment (such as theatre performances and museums).

During the worldwide pandemic, the industry saw both an explosive growth period and a significant struggle. Streaming and immersive content was in high demand, while the arts sector suffered a massive downturn with the heavy restrictions on the population.

Beyond the ABAC position paper, other issues impact the industry and its technology considerations, including the 2023 Writers' Strike and the increasing rollout of accessible AI and Generative AI tools across all aspects of the creative industry's sector.

Therefore, it is clear that, in an ever-changing industry, it is highly important to stay on top of changes and have the much-needed adaptable infrastructure available to meet that ever-changing nature.

Key to the position paper was focusing on the commercial aspects of the industry and how the industry could gain a higher proportion of the global market.

Why the sector is so important

The Creative Industry is comprised of hundreds—if not thousands—of different skill sets. The skills required to be in the industry are vast and highly sought after. These include blending innovation, digital technology, and a wealth of talent. As so many different skills are required, this creates wealth and jobs through the creation of intellectual property (IP).

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A multiplier effect is created from the industry, as its success also creates opportunities for tourism and culture. Wealth built in this sector has an impact on many jobs, from drivers, to directors, to catering. The reach and crossover are vast.

The most important parts of the Creative Industry are those where investment and growth is leading the charge. This is seen in new media and entertainment content, which gives other sectors and industries spillover benefits.

The main sectors of focus include games, film, television, advertising and marketing, interactive (augmented/virtual reality), and location-based entertainment (such as museums). These sectors are growing at different rates, partly due to the level of maturity they have attained in the business cycle.

With the onset of the pandemic, people needed to feel connected to others, which has pushed a dramatic shift in the Industry. A surge in technology trends and uptake of digital technologies has created an opportunity for innovation and growth; and also rapid access to a global market. This has been experienced worldwide, so our goal is to ensure Australia is an active and significant participant in the market.

Beyond this paper, it is clear that the Creative Industry is also impacted by AI technologies and expansion of revenue opportunities via direct-to-consumer commerce and micro content publishing.

The ABAC Position Paper on the Creative Industry

Guidelines

The following principles were devised by the Chair, Deena Shiff, and ABAC Members, Zareh Nalbandian and Vince Pizzica (co-authors of this journal paper), to help position an understanding for the paper of what success and methodology meant, in what most would term a 'unique industry'.

These principles act as guidelines that the Creative Industry Expert Working Group deemed essential for what technological infrastructure needs to do to adequately support the Creative Industry in Australia:

- Encourage global content creators to establish and maintain a presence in Australia;
- Support Australian artists and producers to operate as freelancers or small businesses within the global supply chain;
- Profile innovation across emerging technologies in the newest forms of storytelling;
- Promote a uniquely Australian character to content creation in the newest forms of media.

The following were used as goals for success in terms of the outcomes that could be further enabled via progressive technological infrastructure:

- Hasten the exponential growth of the businesses in the industry and enhance their economic stance in the worldwide economy;
- Correlate the existing digital infrastructure and broadband with upgrades to meet the future needs of the industry;
- Provide methods to overcome not only the current, but also the foreseeable, industry skills deficiencies;
- Provide crossover opportunities that will benefit bordering sectors, in particular to the arts, sports, entertainment, and tourism sectors.

Drivers of change

The paper identified that there are nine key drivers of change in the Creative Industry as validated by data collected and reviewed at the time. Events and trends since the paper was published has validated these drivers:

1. Growth in demand for original content will remain strong beyond the next decade.
2. Traditional content distribution formats and business models will continue the shifts begun in the last decade and accelerated by COVID-19, such as embracing OTT [Over-the-Top] service models.
3. Emerging use of virtual production technologies will grow to affect over 15% of the volume of content produced and have a structural impact on the end-to-end workflow for content creation.
4. Storytelling forms and creativity will evolve into more interactive and multi-dimensional forms as technology and business models match the characteristics that younger demographics find compelling.
5. The purpose for which content can be created will increase opportunities for creative content producers, putting art and storytelling into an increasing range of physical locations (retail, museums, offices, conferences, events, etc.).
6. The skill sets of these talent bases will converge to a much similar combination across *all* sectors of the Creative Industry, as will the other technology capabilities needed to develop assets and Intellectual Property (IP).
7. Cloud infrastructure and cloud-native tools will impact all dimensions of the content value chain, becoming the primary underpinning technology of the industry for both creation and distribution.
8. The commercial nature of the workforce relationships between creative talent and production companies and studios will become more fluid.

9. Integration into cloud-based supply chains is essential for Australian companies to be competitive globally, with barriers to entry in each sector linked to security frameworks.

Out of these drivers, the paper identified two that would have the most impact on the industry. These are interactivity in content creation and storytelling, and location-based experiences. These are predicted to have the biggest impact on growing Australia's share of the global market in the long term. Skills surrounding these will be the most valuable in the future.

Australia has key advantages for guiding the success of the Creative Industry into the newest ways of working and production. These include:

- An outstanding talent pool of professionals and creatives, and a sound academic training system, both operating within a stable political, legal and social system;
- A generous network of production conditions that have excellent support capabilities, combined with a healthy incentive program; and
- The National Broadband Network (NBN), aligned with other broadband capabilities, which ensure a wide geographic connection for most of the population.

It is also important to note there are also significant challenges for the Creative Industry. These include:

- Geographical distance (domestically and internationally);
- Differing time zones;
- Small scale of existing participants;
- Investment and distribution concentration outside of Australia;
- Hyper-competition over limited resources and talent in the lowest parts of the value chain; and
- Shortfalls in skilled labour since the pandemic.

Keys to success

The Chair and ABAC members, with feedback from the Creative Industry Expert Working Group, identified that there are four key success factors:

- Expanded IP ownership in Australia;
- Talent and Skills;
- Crossover of Creative Sectors;
- Investment in digital clusters.

Key 1: Expanded IP ownership in Australia

The Creative Industry, where creative design is the driver of value, centres on the monetisation of the IP that has been created. This has been constant over the years and has not changed in recent times. Create the IP, have it positively geared, and new opportunities will arise.

This key factor is found in many different industries, but what is unique to the Creative Industry is that, no matter how the story is delivered (e.g., via a cinema or a smartphone), decisions around the value content are driven top down by this value chain. The decisions and margins for sustainable investment decisions flow from the top.

One of the main priorities for the Creative Industry is to invest in the development of content IP, which can then flow through the value chain. This should be done with respect to ensuring the decision-making control is held by an Australian business. Throughout all of the supply chain, the decision-making power on investments will always link back to the IP owners, in consultation with local stakeholders.

To expand IP ownership in Australia, the following questions must be asked:

- What is the most beneficial and sustainable method for attracting investments in the Creative Industry that will promote growth and expedite the crossover benefits to the wider economy?
- How can the incentives provided from within the supply chain also have a positive effect on the IP ownership?
- Is it useful to stimulate the infrastructure for worldwide integration that will also assist global content producers and investors to consider moving capital to Australian-sourced content?

Key 2: Talent and skills

Creation and design are very much a human-based skill (although we will discuss the impact of new AI technologies further on). Therefore, the growth of this industry relies heavily on the volume, experience, talent, and breadth of those people working in the industry.

Creating and growing the IP owned by Australians relies heavily on the skills and talents to create it. As a worldwide participant, we must ensure our country is a ***destination*** for the world's leading and aspiring talents. We should not be a ***source*** of creatives who then use those vital skill sets elsewhere.

The challenges facing this key area are as follows:

- A relatively small pool of high-end talent that can be used to drive projects and develop IP that is necessary to expand their business to a higher playing field;

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- A deficiency in graduates and middle-tier people who hold the necessary skills to commence contributing positively immediately from educational institutions;
- Only a small portion of the qualified people entering the industry; more are needed to yield growth.
- A shortage of individuals with the entrepreneurial skills and experience needed to create new and innovative projects to meet demand in emerging sectors and geographies.

Australia has an attractive lifestyle, which can lure overseas talent to our shores and has done so successfully in the past. However, while there are multiplier effects in doing so, there is also a strong urge to self-develop those higher-end skills within the Australian market.

To ensure we have talent and skills in our own marketplace, the following questions must be asked:

- How can we grow and accelerate the postgraduate programs that will increase the skills and therefore value of Australian talent cost effectively, as well as encouraging the industry to influence training at an undergraduate level?
- How can digital clusters be facilitated to build the success of these skills programs?
- What can be provided in the short term in the form of incentives that will have an immediate effect in solving problems in this area?

Key 3: Encourage crossover of creative sectors

The Creative Industry is always expanding to ensure the most wonderful elements of what artists create are a physical experience using leading technology. This brings people to specific locations and boosts other sectors, such as food and beverage, retail, and tourism.

More and more, the industry is creating immersive experiences in venues such as museums, sports venues, and performing arts centres. Success in this area, for both domestic and export industry, requires sector crossover and removal of hurdles between industries. It also relies on investment. While we have the technology domestically, there is still a lack of market share, with most opportunities being offshore.

The industry needs to find ways to encourage crossover between sectors that can assist with removing barriers that limit opportunities. The challenges that still exist are as follows:

- During the pandemic, there was only a small number of immersive experience projects being launched by Australia's tourism destinations;
- We need better ways to efficiently utilise government infrastructure investment to

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nurture an increased partnership between the Creative Industry and other organisations;

- Expanded funding from multiple layers of government is needed for projects in the crossover field of festivals and place-based cultural events;
- What measurable incentives will ensure more crossover projects being proposed by all levels of government and business to increase the growth in the Australian sector?
- How do we better integrate STEM [Science, Technology, Engineering and Mathematics], HASS [Humanities and Social Sciences], and Work Integrated Learning into our educational systems?
- What crossovers will have the best positive impact on export opportunities that will attract global economic value?

Key 4: Invest in digital clusters

Digital clusters are an amazing launch pad for expanding digital services that will create growth for the Creative Industry. Already, there have been fantastic results with digitally focused communities.

Increasing investment in this area will help to develop creative skill centres. This will then increase the community of skilled labour from areas outside the major population zones. In turn, this will lead to a growth in market share for Australia.

The Australian Creative Industry is currently overly concentrated in major capital cities, with one-third of the workforce being in Sydney. Being able to expand to the whole country is a massive opportunity to increase the workforce.

Several states and territories do have plans in place for providing this infrastructure and services in regional areas. We need to focus on areas that can benefit most from this opportunity.

We need to ensure the following to achieve this key goal:

- Better geographical alignment between where the skilled workforce is educated, trained, and wish to live. This is best aligned with more processing, storage, security infrastructure and bandwidth provided. People's proximity to clusters can enable development of interactive skills and content, particularly in regional areas.
    - An example of such infrastructure support is NBN Co's Business Fibre Zones (BFZs). These support businesses of all sizes and in locations across Australia, by reducing the significant variation that has existed in the cost of business broadband services in regional and rural areas compared to Central Business

District (CBD) zones. Eligible businesses within any BFZ that order an enterprise Ethernet service will receive their chosen speed tier and service based on the same CBD-equivalent wholesale charge that is applied to a company based in a CBD zone.

- We need to improve the capacity and capability of facilities within these clusters, to stimulate spillover benefits into other industries while supporting integration into the global supply chain for the Creative Industry. The stated perspective of the position paper is that the supply side of the market will meet the needs of the demand-side opportunities once these digital clusters are identified.

Case Studies in the Position Paper

Rising Sun Pictures

Rising Sun Pictures has been in the industry for 26 years and produces visual effects. Clients are predominantly based in the US, with work filmed in the US, Canada, or UK. Staying connected is critical for them, which has led them to innovate. 'Functional from a distance' is their goal. Rising Sun Pictures states that to innovate around problems and distance is part of being Australian.

Rising Sun Pictures built their own network and tools in order to use digital communications, which were then new. This has enabled them to work better with their clients so they feel connected and enmeshed in their clients' businesses.

Rising Sun Pictures found that developing and accessing talent, particularly in regions, requires a reliable platform. For interactivity, each user needs minimum broadband speeds of 100 Mbps with less than 40 ms latency, as well as relevant experience and a certain level of digital skills.

Rising Sun Pictures believes that Australia needs to focus on overcoming barriers to innovation and entrepreneurship in order to create an attractive market. They believe it is time to change fee-for-service arrangements and to build opportunities for content IP. They look forward to the next forms of entertainment, such as virtual and immersive worlds in, for example, gaming.

VANDAL

VANDAL has been in the industry for 35 years and specialises in creative production using emerging technologies. With an impressive body of work behind them, they have crafted many forms of entertainment, including commercials, interactive installations, projection mapping, virtual reality, augmented reality, digital placemaking, virtual environments, and digital experiences.

VANDAL is a leader in digital media and digital placemaking. They found that investing in people, creative development, emerging media platforms, and pursuing emerging digital technology trends have been beneficial in growing the business and offering new digital media solutions to clients. They believe that regional Australia can become a hub for new development; however, connectivity and good Internet are vital to this outcome.

VANDAL believes that Australian businesses are completely capable of producing new assets and creative IP. However, investment needs to be made in order to protect and nurture the talent pool. Growth and investment in Digital Entrepreneurs are vital to Australia being a leader in the digital landscape.

Animal Logic

Animal Logic[i] is an award-winning digital screen content studio that has been in the industry for 30 years. They have studios in Sydney, Vancouver, and Los Angeles. They have a history of world-leading innovation and are committed to their worldwide audience.

Animal Logic used the challenges from the pandemic to accelerate their technology and to enable their workforce to operative effectively from remote locations. They invested substantially in infrastructure to empower staff to work efficiently and securely.

Animal Logic have identified that staff retention can be challenging, as short-term contracts are common. However, they have developed a training program that provides exposure to the industry for real-world experience. They work closely with education partners to develop their training program and suggest that, linking with universities, they can engage students and provide industry exposure.

Mighty Kingdom

Mighty Kingdom have been in the industry for 10 years. They have grown into a company that has 140 employees and partners in Europe, the US, Israel, and Asia. They have carved a niche of developing games for children, young people, and women. Their popularity and success have attracted production companies wishing to partner with them.

Mighty Kingdom have found their younger staff work easily online and have employed people from regional Australia, from Tasmania to far north Queensland. Due to security frameworks and certification, Mighty Kingdom are unable to work in a shared online space and have therefore created a standalone space.

Mighty Kingdom have identified that fast connectivity is essential to their business and that cybersecurity is costly. They have suggested that there is scope for the government to assist with this issue.

Mighty Kingdom have incorporated machine learning into their game development, which has enabled them to increase the productivity of their processes and allowed for a bigger focus on content development. They are also focused on developing their own IP and are partnering with publishers to share costs and encourage investment.

Interactive Games and Entertainment Association

The Interactive Games and Entertainment Association (IGEA) represents the voice of Australian and New Zealand companies in the video games industry. They do this through advocacy, research, and education programs. Their members range from sole traders to larger global developers.

IGEA believes that fast Internet speeds are critical to helping their members. They also make use of shared studio spaces to collaborate. They have several around Australia, including in Melbourne and Brisbane.

IGEA states that studios in Australia are always in capital cities; however, that is not the case worldwide. They are currently in talks with the government to design regional studios and technology-related platforms. They have also identified that investment in this sector is difficult, especially for new entrants. They would like to see funding support to create and retain projects within Australia.

Greatest Of All Time Interactive

Greatest Of All Time Interactive (GOATi) has been in the industry for 10 years and focuses on game delivery, content creation, and business models for e-sports. They have built their own technology platforms, which has piqued the interest of other businesses.

GOATi has stated that broadband connectivity has been great, which has led them to believe geography is not a problem for them. They are trying to keep their business in Australia and invest in themselves.

GOATi believes that investing in emerging technologies and supporting Australian technology and IP will entice talent back to Australia and help support future talents. They believe the opportunities for overseas work are too enticing for our talented people and we need to ensure they stay in Australia.

GOATi states that, while the game sector has 2000 graduates from Australian game development schools each year, only 2% of them can be hired. They believe Australia could align its approach with those of overseas countries by educating students with tools to go out and develop their own business.

Fika Entertainment

Fika Entertainment[ii] is a virtual production services, solutions, and software company with the ability to automate animation and the visual effects production process via real-time production. More than 80% of interest comes from overseas companies.

Fika states that Internet connectivity and technology are essential for every Australian business. With a base in Queensland, and clients worldwide, they effectively work on a global scale with the right technology. They have suggested that better infrastructure is needed to ensure efficiency moving forward.

Fika has found specific technical skills are difficult to source within Australia and have had to use talents from Canada and Spain to fill vacancies. Fika utilises a virtual server, which is costly; subsidies in this area would help Australian businesses. They have also noted cybersecurity to be a costly expense also.

Queensland University of Technology

QUT was the first university to adopt the ‘Creative Industry' brand back in 2000. It has been a leader in its field for many years. They rely on high-speed Internet connectivity across all campuses and have invested greatly in “digital campuses”. They have students from all over the world.

QUT's programs prepare graduates to work across a range of Creative Industry sectors. They have utilized new technologies in order to successfully move online through the pandemic and reached new audiences.

QUT believes that there is a need to partner with the industry and allow for online modules and short courses, rather than focusing on traditional post-graduate courses. QUT are always developing ways for a more agile curriculum that meets the needs of the industry.

Looking Beyond the Position Paper

Whilst the ABAC position paper was delivered in March 2022, the pace of the shifts and market developments impacting the Creative Industry have continued to gain pace. At this point, nearly two years since its findings were presented, it is interesting to briefly describe:

1. How the trends and changes can be mapped back to what was described in the position paper and what impacts the position paper has had within the Creative Industry in Australia over this period; and

2. Delve a little further into intervening emergences of Generative AI and Accessible AI tools, which is the sort of disruption which accelerates the shifts identified in the position paper but perhaps can damage the very structure of the downstream business structures within the Creative Industry.

It is important to note that the delivery of the position paper to ABAC occurred just as the Federal Government was changing administrations, which inevitably creates a period of transition as policy priorities adjust. However, 2023 also saw probably the most destructive industrial action that the Media and Entertainment industry has ever experienced, which coincided with financial markets completely resetting the metrics around valuation of Entertainment businesses.

While the use of AI technologies is not new across many industries, late 2022 saw the deployment of Generative AI tools worldwide. This motivated great excitement and, at the same time, great concern around what would be the impact of these tools on the future of our industry.

Has the Position Paper contributed to the discourse in this period?

It was timely that the position paper accurately anticipated the trends and impacts that occurred in 2022 and 2023, given the discourse and debate that was drawn out of the participants and leaders in the industry during its writing. The dramatic drop in share prices of companies like Disney and Netflix, because of the subscription business models they have embraced, was the trigger of a new phase of industry restructuring. Whilst there is ample scope for further examination of this topic alone, the main impact, which the position paper had drawn focus towards, was the increased importance of ownership of Creative IP over the execution of services in the building of creative content.

Reduced return on investment for distribution of entertainment caused by increasing market risk, shifts in consumption and a drop in the cost of distribution also support the aim of the position paper to drive crossovers between sectors, since this will increase returns from investments in skills and asset production.

The extended strikes in the US by the Writers Guild of America (WGA) and Screen Actors Guild (SAG/AFTRA), which effectively shut down the industry in many parts of the world, will also have lasting and permanent impacts on industry structure. Both strikes were aimed at restoring the ability of their members to sustain a career in the industry and effectively reset the cost structures of talent in content production. A consequence of this will be less volume of work funded by the existing industry leaders as they search to control costs and find better returns. Interestingly, this can also have a positive impact on demand for talent when coupled with the shifts in industry structure and the forms of media being monetized. More value can be driven by pushing ownership of the IP back towards the creators of that IP – a trend that was clearly identified in the position paper and demonstrated by the rise of the so-called Creator Economy, which industry estimates indicate has already >50 million people globally with somewhere between 5 and 10% of these creators earning a liveable income from their work (Arbanas, 2023).

However, probably the biggest contribution the position paper has made to these issues has been the elevation of these topics in the minds of leaders within and around the industry at this precise time of change. Enabling Australians to grow their share of this industry as it transforms will require leadership from those executives, artists, and investors to recognize the opportunities and gaps that exist. In feedback from many across the industry in Australia, it is clear that the position paper has contributed to the actions being taken in many areas, including within the academic domain with the newer generations of creative talents embracing its recommendations and goals.

AI tools & Generative AI in the Creative Industry: friend or foe?

As previously noted, the recommendation of the position paper around investing in Regional Digital Clusters was in large part around recognizing the emergence of AI tools and significant productivity improvements alongside collaboration between local and globally located cells of talent. However, the reaction in the market to the dramatic demonstration of Generative AI capabilities accelerated concerns at its potential to take away jobs.

Opportunities that have been flagged at a rapid and global scale include:

- Improving creative ideation, production and manufacturing processes (Law, 2023);
- Rapid generation of personalized content based on individual user preferences (Davenport & Mittal, 2022);
- Enhancing cross-sell and upsell opportunities for direct-to-consumer content owners and creators, retailers and consumer packaged goods companies (Chui *et al.*, 2023);
- Collecting insights to improve product offerings (Chui *et al.*, 2023);
- Transforming industries and creating job opportunities/upskilling (Hiltbrand, 2023);
- Advancements in AI-driven creative workflows and tools (Preeti Padma, 2022).

Concerns that are currently being cited:

- **Deepfakes or look-alikes/sound-alikes**: Generative AI has led to the rise of deepfakes, creating realistic but entirely synthetic media, which poses ethical and security challenges for existing IP owners and performers (Dilmegani, 2023);

- **Data Privacy**: Generative AI models require vast amounts of data, potentially risking breaches of personal and proprietary information (Ortiz, 2023);
- **Cybersecurity**: The technology can be exploited maliciously, such as creating phishing content that is highly convincing (Ortiz, 2023);
- **Copyright Issues**: Generative AI's ability to produce content leads to potential copyright infringements (Lawton, 2023);
- **Intellectual Property Concerns**: Widespread adoption of generative AI creates challenges related to copyright and ownership rights (Mahadik, 2023);
- **Loss of work and Deteriorating Work Conditions**: Generative AI might exacerbate poor working conditions in the Creative Industry, especially for routine creative tasks (Flew, 2023). Also, there are concerns about mass layoffs that appear to be occurring in various sectors within the Creative Industry.

The 2023 WGA Strike has been a response to the potential impact of Generative on writers and also on many other creative practitioners. The strike raised the following concerns:

- AI was being used by studios as a tool to avoid paying union members (Silberling, 2023);
- Hollywood writers were in a battle over being exploited by AI, eventually securing a new contract with strong guardrails addressing the AI issue (Anguiano & Beckett, 2023);
- There were worries that studios would downgrade screenwriters' roles to merely reworking scripts produced by AI (Coyle, 2023). This was one of the factors triggering the Writers Guild of America's strike (Merchant, 2023).

Overall, many see that embracing AI is unavoidable, much as were other key technological leaps, like the emergence of printing in the 16th Century, the introduction of the train, the plane or motor cars, and in more recent times the introduction of the Internet. This type of major change creates disruption and loss and, in equal measure, opportunities and innovation.

There will always be a desire for the authentic 'human touch or connection' in creative works and content experiences for a multitude of reasons. However, it is clear right now that AI is greatly beneficial as part of the current creative ideation, production, and commercialisation process. For example:

- **Large-scale creative projects and businesses** (e.g., feature films and TV series). The production, facilities and operational elements that support the making and marketing of these projects will look to further embrace 'process' efficiencies, analytics and effectiveness to help improve their budgets (and thus profits), and the quality and effectiveness of content landing on audiences. Since it is still common practice for the commissioning and promotion to draw upon the personal heuristics of executives, which leaves decision making prone to certain biases around the market rather than the more common industry practices adopted in e-commerce, new AI tools in processes can have immediate benefits.
- **Independent, smaller/fragmented-scale creative projects and businesses** (e.g., TikTok and YouTube creators, writers, performers, gaming). AI capability is also paving the way for what some would view as the welcome fragmentation and democratisation of creating and commercialising creative content and experiences. Deloitte's recently released '2023 Media & Entertainment Industry Outlook' (Arbanas, 2023) and other publications (e.g., Koerner, 2023) talk of the relentless rise of the new creator economy that is successfully commercialising its art and content direct to it audiences globally without needing to rely on large budgets and/or 'top of the funnel gatekeepers' (i.e., big studios and distributors) to get there. Instead, they are leveraging global publishing platforms like YouTube, TikTok, Steam, Unreal, and Cameo that allow for greater creator and IP autonomy and authentic connection with their audiences. The concept of a direct-to-consumer business model in the Creative Industry is not new, but it is evolving, and AI will only help creators and originating IP owners evolve faster with it.

Thus, as the ABAC position paper asserted, technological infrastructure and various resources need to be progressive in this country in order to ensure that Australia is able to compete and be positioned globally in not only the Creative Industry but all industries.

Conclusion

The winds of change in the global Creative Industry are launching tremendous opportunities and threats for Australian companies and talent. The window to seize a larger share of the global market whilst also securing more certainty of returns for existing businesses is the next five years; and the path to success clearly centres on more ownership of Creative IP in Australia, by Australians. There are many ways for the Australian Creative Industry to be supported by the Federal Government. Investing in infrastructure is vital to how Australian businesses can lead in this emerging new market around Creative IP and the business models in its value chain. In this modern, post-pandemic world, with the rollout of accessible AI tools and AI generative technologies, this is an especially important priority. These newer technologies are allowing creators of original intellectual property and established brands to explore new revenue opportunities that leverage content production, publishing, and sales technologies with the potential of tapping into 'direct to consumer'. Without reliable and fast Internet connectivity, most businesses will not be able to work, compete, adapt, innovate, and sell on a global scale.

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Endnotes

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[ii] The first author was the Founding CEO of Fika Entertainment.

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Fusion-Based 2.5D Face Recognition System

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Abstract: Face recognition is the dominant biometrics system used to authenticate an individual's identity in various applications. Most commercial face recognition systems rely on 2D face images, but the changes in the environment lighting and a person's posture affect the accuracy of the 2D face recognition systems. Hence, the 2.5D face recognition system arises as the solution to eliminate the drawbacks of the 2D face recognition system. The depth feature in the 2.5D data (depth image) provides additional information that can help to improve the accuracy and robustness of 2.5D face recognition systems, particularly in challenging scenarios. This paper proposes a fusion-based approach for the 2.5D face recognition system to enhance the system's performance, where feature fusion involves the combination of features extracted from the depth image. Gabor-based Region Covariance Matrices (GRCMs) that serve as face identifiers combine the depth and texture images in the structure of a covariance matrix. Several experiments on different fusions have been conducted in the Face Recognition Grand Challenge version 2 (FRGC v2.0) database. This paper shows that the max-min fusion applied to the surface normal (y-direction) and the mean curvature has achieved the best accuracy rate of 93.66% among the other fusion approaches used.

Keywords: fusion-based approach, depth image, 2.5D data, Gabor-based Region Covariance Matrices, 2.5D face recognition

Introduction

Face recognition has attracted the interest of researchers, since it enables non-intrusive detection, identification, and authentication without seeking the individual's knowledge or consent. Researchers have recently been passionate about investigating the 2.5D face recognition system considering that, although the 2D face recognition system has made

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significant improvements in the last decade, the effectiveness of the findings is still heavily reliant on lighting conditions and a person's position. The disadvantages of 2D face recognition, such as lighting changes and difficulty with facial emotions, could potentially be overcome using 2.5D face recognition. Furthermore, by gathering less data and processing it more effectively, 2.5D face recognition boosts the reliability of 3D face recognition, which is time-consuming and costly. Each pixel — x and y on the camera's perspective — in a 2.5D image contains just one depth value — z — which shows its distance from the camera's scene. As a result, the 2.5D data accurately depicts the 3D structure, uninfluenced by variations in colour or lighting conditions (Chong *et al*., 2016).

The Gabor-based region covariance matrices (GRCMs) as face identifiers have gained interest and are frequently used in facial recognition systems to perform feature extraction. GRCM works in a way that integrates the Gabor feature with the face picture in the covariance matrix. The covariance matrix is an essential component of the region covariance matrices (RCMs) because it is able to gradually combine distinct image data while maintaining the connection among the features of the image (Chong *et al*., 2014). In this paper, GRCM is used to merge the depth and texture images, which are presented in sequential and direct addition methods, respectively.

In this work, a fusion-based 2.5D face recognition system is suggested to enhance the accuracy rate of the system. The typical approach for forming feature fusion in a face recognition system is by combining two features or merging two features using certain algorithms. The feature fusion technique, which generates more informative features, could strengthen the reliability of 2.5D face recognition. Several studies are carried out in order to determine the optimum fusion technique that produces the maximum accuracy rate and raises the system's efficiency. The experimental findings for each fusion strategy have been documented, along with the best and worst fusion techniques that were defined based on the results.

The objectives of this paper to overcome the constraints of the present 2.5D face recognition system are: (1) to investigate the different features of 2.5D data; (2) to study the fusion techniques of the 2.5D face recognition system; and (3) to conduct experiments in order to evaluate the system's effectiveness.

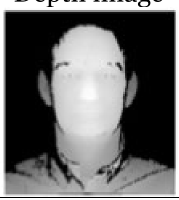
Literature Review

Face recognition

A face recognition system is a form of biometric security that uses facial biometric data and patterns to authenticate a person's identification. Two-dimensional (2D) face recognition represents a type of facial recognition technology that leverages the advantage of the two-dimensional geometry of a human face. The public widely accepts the 2D face recognition system, and the gadget used to capture the image is less expensive than a 3D face recognition system. The main drawback of 2D face recognition is that the accuracy of the output is strongly reliant on the illumination and postures of an individual in the captured picture or photo. With these constraints, three-dimensional (3D) face recognition is presented as a solution to the dilemma of 2D technology. A 3D face recognition system outperforms a 2D facial recognition system because it can gather additional data (surface normal, curvature) from a person's face and is less susceptible to lighting. As contrast, the primary technical limitation of 3D facial recognition techniques is the acquisition of a 3D picture, which normally demands a range camera, which is costly.

2.5D face recognition techniques have been developed to address the high-cost issue in 3D face recognition systems. 2.5D face recognition looks to be an effective technique that makes use of depth (range) face images. 2.5D data is a "digital image" created by 3D face scanning that represents a certain position's face look. To create a comprehensive 3D face model, a large amount of 2.5D data is collected from various views in 3D facial recognition technology. The 2.5D face recognition system requires just one use of the 2.5D data. 2.5D face data, which stores three-dimensional coordinates — x, y, and z — is perfect for the structure because it provides a depth value, the z-coordinate, which is a necessary component of a 3D model. Each 2.5D face data set is translated into a depth representation for computational efficiency. The depth value, which is the z coordinate, is kept in a 2D matrix structure known as a depth image (Chong *et al.*, 2019). Table 1 shows a comparison of all three forms of face recognition.

Table 1. Differences between three types of face recognition (2D, 2.5D and 3D)

Face Recognition Technology	**2D**	**2.5D**	**3D**
Image Format	Texture-based image 	Depth image 	3D facial model 
Pre-processing Element	Easy	Middle	Hard
Cost of Gadget	Cheap	Middle	Expensive
Coordinates Involved	Coordinates x, y	Coordinates x, y, z	Coordinates x, y, z
Limitations	Posture, facial expression, lighting	Posture, facial expression	Posture, facial expression

Feature fusion in face recognition

Bodla *et al.* (2017) presented a novel deep heterogeneous feature fusion network strategy for blueprint face recognition that employs complementary substance in features provided by several deep convolutional neural networks (DCNN). In addition, a feature fusion approach that merges two independent feature sources to represent a face image with the use of a Canonical Correlation Analysis (CCA) algorithm has been proposed by Nhat & Hoang (2019).

Dutta *et al.* (2021) suggested a complement components (CC) mathematical model for face elements based on depth points extracted from the depth image. Furthermore, an improved Region Covariance Matrix (RCM) for the 2.5D face identification system is implied to boost the recognition efficiency of the system by overcoming the vanilla RCM's shortcomings in obtaining distinctive features from face photos; and failure in recognition of faces is presented by Chong *et al.* (2017).

Region covariance matrix approaches

Tuzel *et al.* (2006) suggested the Region Covariance Matrix (RCM) approach, which gives a new area classifier and demonstrates how it could address two problems: recognition of an object and texture categorising. This approach is represented as a covariance matrix to combine numerous picture numbers produced within a sole image region. The RCM is implemented to define the characteristics of the region. However, RCM shows poor results when implemented in a 2D face recognition technique, proving that it is unsuitable to be employed as a face classifier in 2D technology.

As a result, Pang *et al.* (2008) recommended Gabor-based area covariance matrices (GRCMs) as face descriptors to identify a human face. The Gabor features include more due to their strong spatial localisation, size, and position consistency. By including Gabor characteristics in the calculation of area covariance, the RCM's descriptiveness, along with its differentiating ability, may be significantly improved. Thus, the proposed GRCM approach has the potential to generate excellent face recognition results.

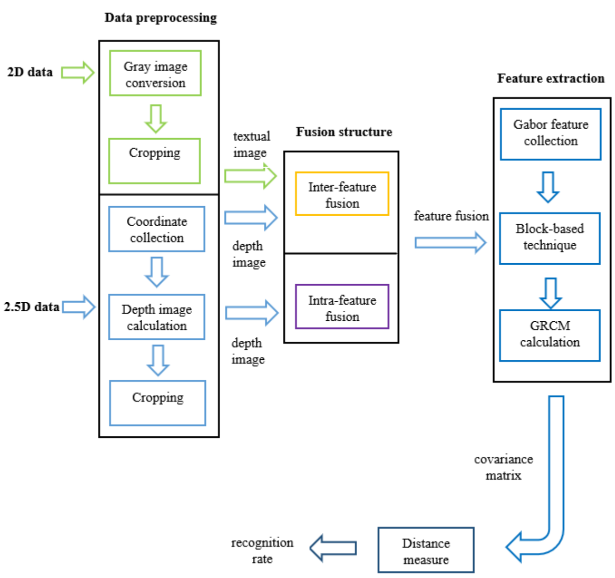


Figure 1. The proposed 2.5D fusion-based face recognition system

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Research Methodology

Based on Figure 1, the suggested approach consists of four phases: the data preprocessing stage, feature fusion stage, feature extraction stage, and distance measure stage. Note that the 2D and 2.5D partial data are pre-processed before being combined to generate the inter-feature fusion.

Pre-processing of data

To get started, the partial 2.5D and 2D face images need to be pre-processed to standardise the size, minimise noise, and establish zero mean normalisation of the image. The pre-processing processes of 2.5D data involve the collection of coordinates, computation of depth image, cropping, normalising, and standardising of faces in order to build a normalised depth picture. The x, y, and z coordinates are collected from each data point in 2.5D data. To extract a face region from the partial 2.5D data, the unnecessary background setting is removed. This depth image is generated by interpolating the z-coordinate retrieved from the rectangular grid in the x-y plane. Cropping the picture according to the location of both the eyes and the mouth yields a canonical depth image. The standard depth image is normalised via a typical standard adjustment, which rescales the data to ensure the variance and mean are set to zero. Figure 2 shows the procedure of the pre-processing steps for 2.5D data.

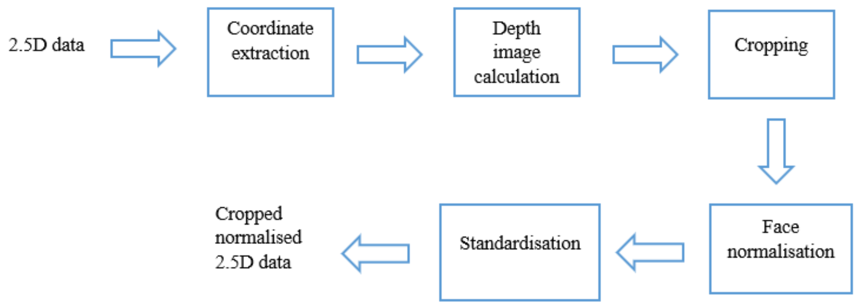

Figure 2: The procedure for the pre-processing of 2.5D data

The 2D pre-processing steps include grayscale image computing, image cropping, and normalising along with standardising faces. The 2D face image data is converted into a grayscale image. The textual data is then manually cropped based on the middle of the lips and both eyes. Following that, the standard normal transformation is employed to normalise the canonical texture image depending on the locations of the mouth and eyes. The standardisation phase aims to achieve zero mean and unit variance. Figure 3 illustrates the process of pre-processing for 2D data.

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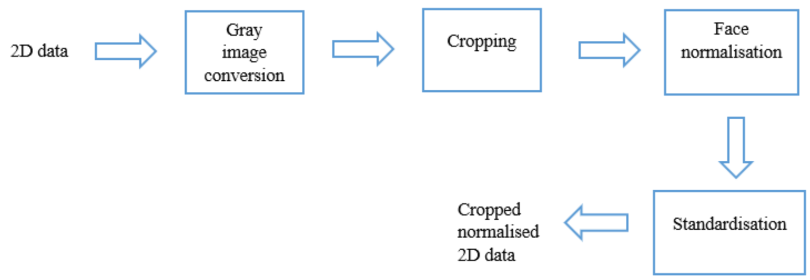

Figure 3. The procedure for the pre-processing of 2D data

Feature fusion

Feature fusion represents the integration of features from different parts or phases of an entity. In a face recognition system, feature fusion involves combining two distinct techniques; merging and mixing the methods improves the system's accuracy and dependability. Different facial traits could represent various parts of a person's facial characteristics, and employing these unique characteristics may enhance one's facial recognition. Facial recognition techniques extensively employ feature fusion to boost the system's recognition accuracy rate (Talab *et al.*, 2022). In this section, different feature fusion methods including inter-feature fusion, intra-feature fusion, and fusion integration methods have been used to fuse features.

Inter-feature fusion is known as one of the feature fusion methods in a face recognition system. The process of inter-feature fusion includes merging data from several different characteristics or features collected from various face modalities or portions. This fusion approach attempts to enhance the overall effectiveness of the facial recognition system by using complementary information from diverse sources. For instance, this method merges different types of information, such as a 2D image with a depth image, using various fusion techniques, such as max fusion, min fusion, and many more.

By contrast, intra-feature fusion differs from inter-feature fusion in the way that it aims to integrate data through a sole feature description. In order to gather more accurate and reliable information, it requires acquiring several descriptions from a single area of the face. This fusion method seeks to improve the description of a single feature through various orientations and sizes. For example, some properties can be extracted using the depth image's comprehensive collection of face topological data, such as the curvature feature.

Furthermore, a specific kind of fusion technique that combines previously fused data once again is referred to as the fusion integration approach. This fusion technique aims to combine and gather more discriminative features from the fused data to boost the system's performance. For instance, this fusion method is generated by integrating the intra-feature fusion with another intra-feature fusion using different fusion approaches, such as the sum

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rule, max-min fusion, and others. The comparison between inter-feature fusion, intra-feature fusion, and fusion integration is exhibited in Table 2.

Table 2. Comparison between three types of feature fusions

	Inter-Feature Fusion	**Intra-Feature Fusion**	**Fusion Integration**
Structure	Combination of the depth image with 2D image	Features produced from depth image, such as mean curvature, surface normal etc.	Combination of the intra-feature fusion with another intra-fusion feature
Number of fusions occurring	One	One	Two
Involves fusion technique?	Yes	No	Yes

Inter-feature fusion

Inter-feature fusion combines features extracted from several raw images to boost the system's accuracy. A novel fusion dataset is developed by combining the two distinct characteristics provided by the textual data and the depth data. Minimum fusion is known as one of the fusion strategies. This technique creates a fused image by selecting the pixels with the minimum data point (Kaur *et al.*, 2021). For example, Equation (1) shows the use of minimum fusion (*Mn*) with the depth image (A) and the 2D image (B).

$$Mn = Min(A, B) \tag{1}$$

Additionally, maximum fusion (*Mx*) is another fusion approach that separates high-intensity pixels from images to form a combined image as illustrated in Equation (2) (Kaur *et al.*, 2021).

$$Mx = Max(A, B) \tag{2}$$

The Max-Min fusion (*M*) represents one of the fusion techniques that utilises the values retrieved from both the maximum and minimum fusion. The fused picture is created by identifying the average scores of the components with the lowest and highest scores within the entire input picture (Kaur *et al.*, 2021).

$$M = Max(A, B) - Min(A, B) \tag{3}$$

The sum rule can also be applied in the system as one of the fusion approaches to increase the system's accuracy. The sum rule method adds up the features to form a new feature.

Intra-feature fusion

Intra-feature fusion represents another form of feature fusion approach to increase the reliability of the system. The depth image itself collects an extensive amount of face topological information, from which these characteristics may be retrieved for intra-feature fusion.

http://doi.org/10.18080/jtde.v12n1.770

Surface normal represents one of the intra-feature fusion approaches to boost the accuracy rate of the face recognition system. Three sorts of data from axes x, y, and z could be extracted from an individual's face, since the 2.5D face photos often collected in a point-cloud form are made up of x, y, and z coordinates for a face. The vectors with the values Nx, Ny, and Nz represent the three separate data sets collected from the face (Vezzetti & Marcolin, 2012). To generate a new equation, the sum rule of the surface normal (SN) is employed for these acquired different surface normal points, as defined in Equation (4).

$$SN = Nx + Ny + Nz \tag{4}$$

Besides surface normal, an example from among the intra-feature fusion methods used to improve the effectiveness of the face recognition system is curvature as a 3D feature. The minimum and maximum curvatures are the two basic curvatures used to characterise the local shape of a surface. The parameter k_1 is defined as the maximum curvature, while k_2 is defined as the minimum curvature. Then, mean curvature can be computed after getting the maximum and minimum curvature values (Vezzetti *et al.*, 2014). Mean curvature (H) is the average of the minimum (k_2) and maximum (k_1) values, where $k_1 > k_2$ as shown in Equation (5).

$$H = \frac{1}{2}(k_1 + k_2) \tag{5}$$

Furthermore, the Gaussian and mean curvature represents the intrinsic and extrinsic geometric characteristics of the surface. Gaussian curvature (K) is determined from the surface's differential geometry; it remains local, intrinsic, and preserved by affine translation (Vezzetti *et al.*, 2014). It is the product of the two essential curvatures, as displayed in Equation (6).

$$K = k_1 k_2 \tag{6}$$

Fusion integration approach

The fusion integration approach is a type of fusion method that fuses the fused data again. Fusion integration in this section is generated by combining the intra-feature fusion with another intra-feature fusion retrieved from the previous section. For instance, the best recognition rate, which is achieved by the surface normal (y-direction) in the intra-feature fusion, is combined with the second highest recognition rate, which is the surface normal (average), to form a new fusion (fusion integration) and it has been examined through various fusion methods such as using Sum Rule, minimum fusion, and others. There are many types of fusion approaches that can be used in order to increase the system's efficiency and boost the system's performance.

http://doi.org/10.18080/jtde.v12n1.770

Feature extraction

Face recognition necessitates feature extraction that involves segmenting facial pictures, generating images, and scaling faces. Gabor-based region covariance matrices (GRCMs) are frequently employed as face descriptors in facial recognition systems nowadays. Gabor features have more spatial localisation, dimension, and alignment precision than first- and second-order grades, and hence involve more information. By including Gabor characteristics in the calculation of covariance area, the RCM's descriptiveness, along with its differentiating ability, may be significantly improved (Pang *et al.*, 2008). Consequently, the proposed Gabor-based RCM approach yields satisfactory face recognition scores. The region covariance matrix is generated by combining the feature mapping function via Gabor features, as indicated in Equation (7), where R is the fusion technique applied (Chong *et al.*, 2016).

$$\phi(R, x, y) = [x\ y\ g_{00}(x, y), g_{01}(x, y), \dots, g_{74}(x, y)\ ] \tag{7}$$

The collection of Gabor features, the use of a block-based strategy, and the calculation of the GRCM are the three processes that make up this phase. Equation (8) describes the Gabor-based region covariance matrix (GRCM). The Gabor (G) dimensions are determined by the size of the covariance matrix (42×42 dimension), which is formed by multiplying the x and y coordinates of the pixels using a 40 Gabor wavelet and adding up the results (Chong *et al.*, 2016). Figure 4 shows the process of generating the GRCM.

$$G \in \Re^{42\times42} \tag{8}$$

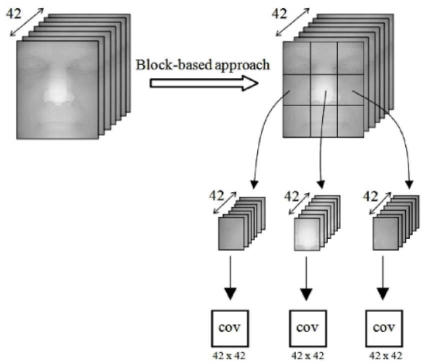

Figure 4. The generation of GRCM map

Distance measure

The distinctive features of a person's face, such as whether the person is male or female, whether the person is wearing glasses or not, and many other things, could be determined and categorised using distance measure metrics. The Euclidean distance is employed to calculate the distance between two coordinates in 2D space and to determine the exact distance between parameters in the space of N dimensions along a straight line. Therefore, in facial recognition,

http://doi.org/10.18080/jtde.v12n1.770

smaller values indicate a higher level of similarity between two faces. The Euclidean distance computation equation is shown in Equation (9), assuming that the image's face characteristic is to be represented as $P = (x_1, x_2, \ldots, x_{128})$ and the training sample's facial traits are to be identified as $Q = (y_1, y_2, \ldots, y_{128})$:

$$PQ = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_{128} - y_{128})^2} \tag{9}$$

The Euclidian distance measurement, unfortunately, is only precise on a straight line. The recognition rate is expected to be low when employing the Euclidian distance technique, since the human face involves numerous curve lines.

Tensor Manifold is a non-Euclidean space that is flat locally but curved globally. Each covariance matrix associated with GRCM remains uniquely equal to a single location on the Tensor manifold. The Euclidean distance measures the distance between two points (array-based data) in Euclidean space, while the particular distance measure calculates the distance between two covariance matrices (matrix-based data) within the Tensor manifold (Chong *et al.*, 2014). The space between two GRCMs must take into account the geometric qualities of the manifold, a measurement termed geodesic distance, which represents the shortest distance between two GRCMs. The tensor manifold yields greater accuracy than Euclidean distance since it does not reside in Euclidean space (Chong *et al.*, 2016).

Cholesky Distance (CHOL) is recognised as a re-parameterisation measurement that divides each GRCM evenly into a mixture of a lower matrix with a triangle form and its transpose (Chong *et al.*, 2014):

$$(P, Q) = \parallel L_P - L_Q \parallel_F \tag{10}$$

LogDet Divergence distance (LD) represents a collection of information-theoretic approaches. It is a kind of matrix difference that determines how far away two GRCMs are (Chong *et al.*, 2014):

$$(P, Q) = log\left|\frac{P-Q}{2}\right| - \frac{1}{2} log|PQ| \tag{11}$$

where $|.|$ is the determinant of the matrix.

Another of the metrics used to determine distance is the Affine Invariant Riemannian Metric (AIRM). This approach employs a similarity measure based on the tensor manifold, which includes eigenvalue decomposition, exponentials, logarithms, and square roots (Chong *et al.*, 2014).

$$(P, Q) = \sqrt{\sum_{i=1}^{5} ln^2 \lambda_i(P, Q)} \tag{12}$$

http://doi.org/10.18080/jtde.v12n1.770

where the eigenvalues of P and Q are represented by $\lambda_1, \dots, \lambda_5$.

Additionally, the Log-Euclidean Riemann Metric (LERM) is another method for calculating distance. This method uses Euclidean metrics logarithms' space to compute the distance between two GRCMs. LERM represents a standard measurement that is employed within the tensor manifold in a face recognition system (Chong *et al.*, 2014):

$$(P, Q) = \| Log(P) - Log(Q) \|_F \tag{13}$$

where Log(.) indicates the logarithm of the matrix and $\|\cdot\|_F$ represents the Frobenius norm.

Recognition rate

Every biometrics system must determine the accuracy rate of its method because it illustrates the system's accuracy and reliability. The true positive (TP) is the number of times the technique correctly identifies the same individual in two different images. The true negative (TN) denotes the number of times the algorithm properly distinguishes between two distinct persons in the images. By dividing the total number of correctly identified images (TP and TN) with the total number of images, the recognition rate is determined:

$$Recogniton\ rate = \frac{(TP + TN)}{(total\ no.of\ images)} \times 100\% \tag{14}$$

Furthermore, one method for evaluating the efficiency of the system is to measure the amount of time in seconds that the system utilised to complete the recognition procedure of the individual from the database. A more rapid computation time used by the system results in an increase in the effectiveness of the system.

Experiments and Discussion

Face dataset

The Face Recognition Grand Challenge version 2 (FRGC v2.0) is being used in this paper. Every time a person's biometric information is collected, a subject session is taken, including four controlled still images, two uncontrolled still shots, along with a 3D picture of an individual. The collection of data in FRGC v2.0 involves 466 individuals, 4,007 subject sessions, and 32,056 recordings.

Experimental setup

A part of FRGC v2.0 is implemented, which consists of a total of 254 subjects. A total of 16 images, 8 images from both the 2.5D partial data and 2D data, were selected randomly for each individual, corresponding to a total of 4,046 images. Each image has been resized and standardised to 73×61 pixels. The pixel intensity of the picture has been adjusted to a zero mean and zero unit variance. The GRCM's Gabor kernel is set up with the following parameters: $k_{max} = \frac{\pi}{2}$, $\sigma = \pi$, $f_v = \sqrt{2}$. When the pixel position (x, y) information is added, a Gabor wavelet with the dimensions 40×40 becomes 42×42. Two distinct fusion schemes, such as intra-feature fusion and inter-feature fusion, along with fusion integration methods, including max fusion, min fusion, max-min fusion, and sum rule, have been examined. Besides, the 2D image, depth image as well as feature fusions use the block-based GRCM in the feature extraction stage.

Results and analysis

Results of inter-feature fusion

Figure 5 exhibits the recognition rate of the several inter-feature fusions based on sum rule, min fusion, max fusion and max-min fusion, using difference distance measures. Based on Figure 5, sum rule with the combination of both the depth image and the 2D image scores the most significant recognition rate using LERM at 93.31%. The sum rule outperforms the single depth image because it incorporates characteristics from both the depth and 2D images. In addition to the sum rule, methods like min fusion, max fusion, and max-min fusion achieve better performance than a depth image. This demonstrates that inter-feature fusion approaches outperform a sole depth image for most distance measures.

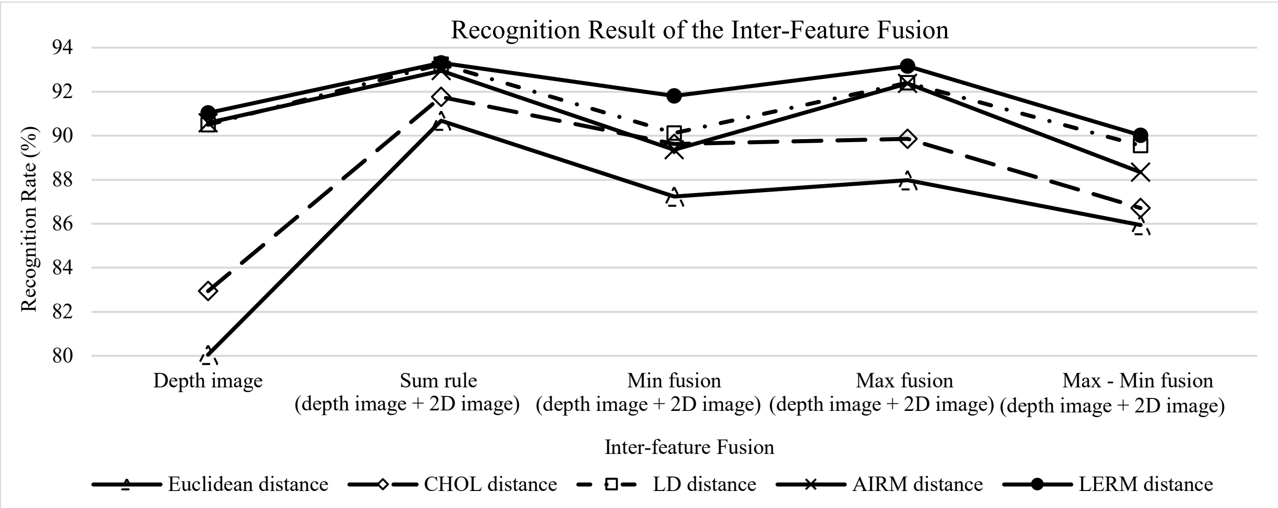

Figure 5. Recognition rate (%) of the inter-feature fusion

The computation time for each inter-feature fusion is shown in Figure 6. It can be seen that every inter-feature fusion utilises the shortest amount of time to compute the recognition rate using Euclidean distance. However, the recognition rate for each inter-feature fusion using Euclidean distance is the worst compared to the other distance measures, as shown in Figure 5. In contrast, although the computation time of the LERM distance to calculate the recognition rate is the longest among the other distance measures as shown in Figure 6, but the recognition rate of the majority of the inter-feature fusion scores the highest performance in LERM distance, as illustrated in Figure 5.

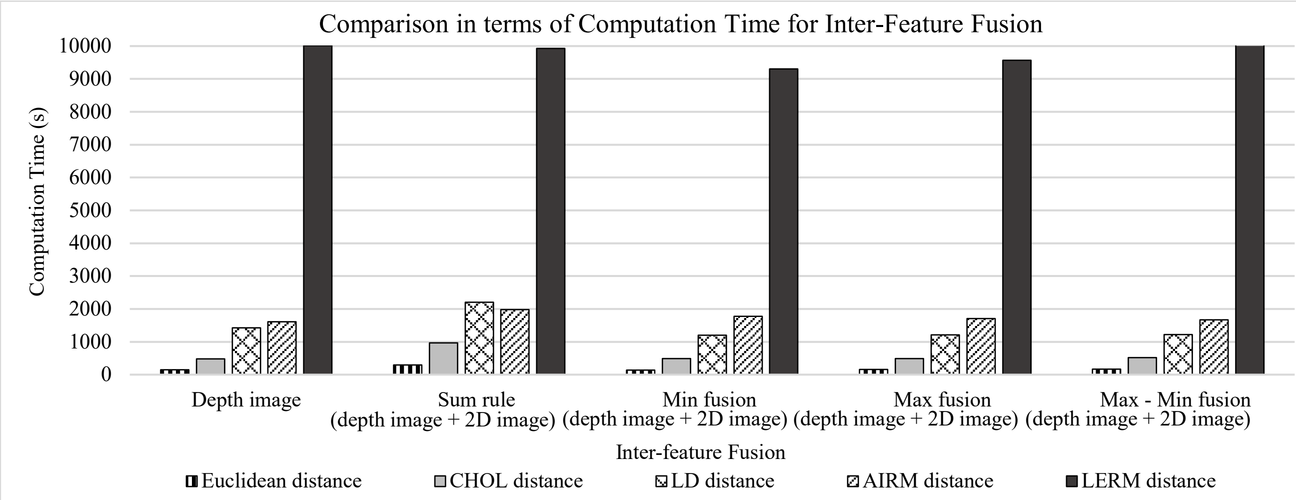

Figure 6. Computation times for inter-feature fusion

Results of intra-feature fusion

Figure 7 demonstrates the recognition rate of the intra-feature fusions. It shows that the majority of intra-feature fusions perform better than the depth image. The y-direction surface normal holds the highest intra-feature fusion performance, especially in the LD distance measure, where it obtained the accuracy rate of 93.32%. Contrarily, Gaussian curvature yields the poorest performance when contrasted with the other intra-feature fusions. Hence, it can be concluded that Gaussian curvature is not able to perform well in 2.5D face recognition.

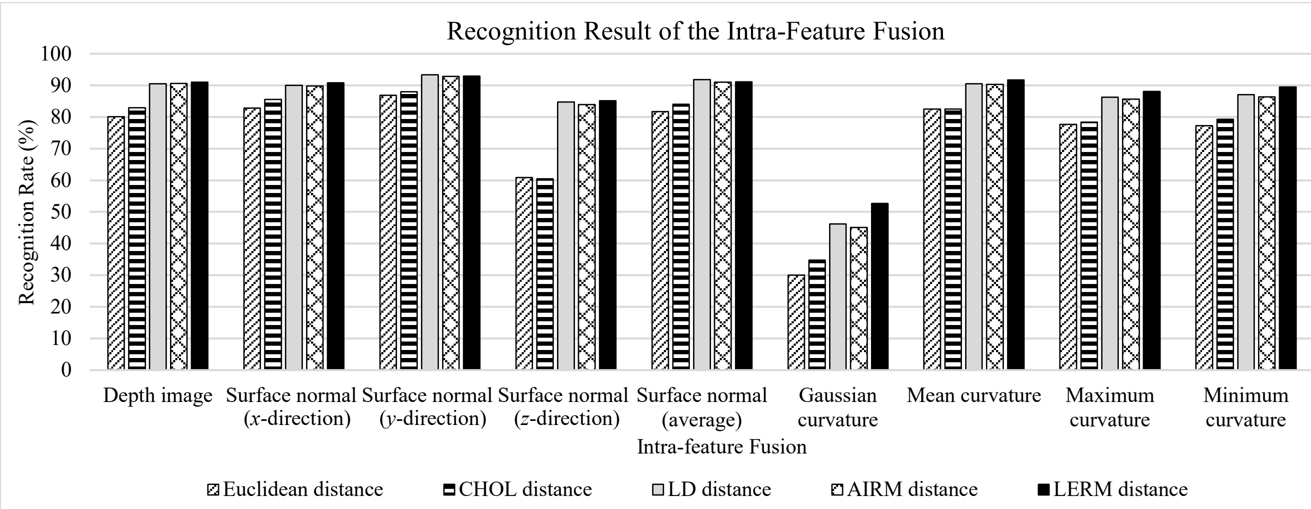

Figure 7. Recognition rate (%) of the intra-feature fusion

Additionally, the recognition rate for the surface normal in the x and y directions is almost identical. However, the accuracy rate for the surface normal in the z direction appeared to be the lowest among the three directions in the surface normal. Figure 7 has proven that summing the surface normal in the x, y, and z directions produces the best results. Moreover, single curvature (curvature minimum or curvature maximum) is not able to compete with the mean curvature (combination of curvature minimum and curvature maximum) as it contains the feature integration of these two curvatures.

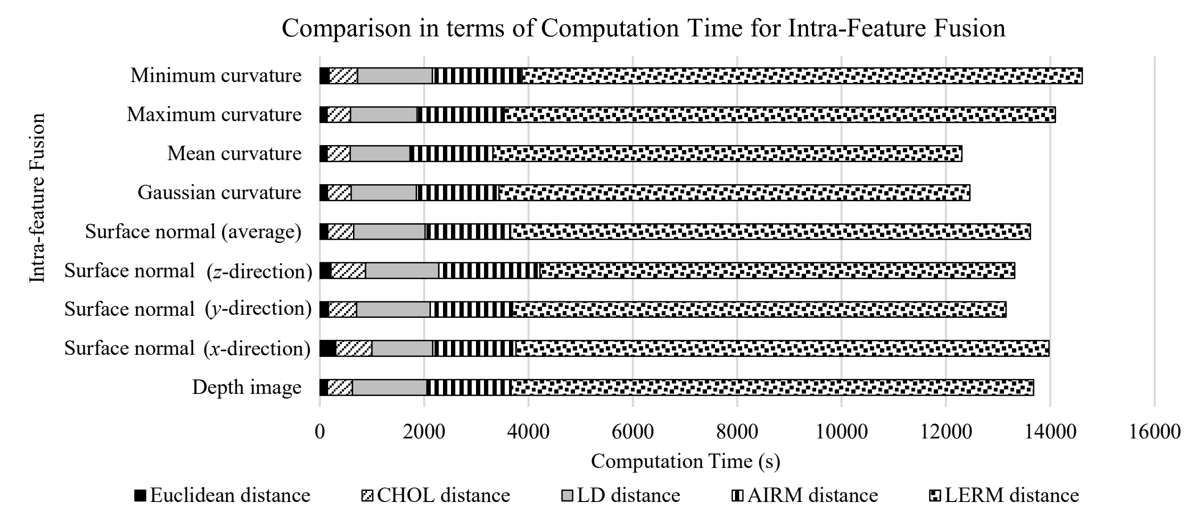

Figure 8 Computation times for intra-feature fusion

Figure 8 displays the computation time for each intra-feature fusion. The total computation time of each distance measure used to calculate the recognition rate in intra-feature fusion is almost identical with the inter-feature fusion. Figure 8 has proven that every intra-feature fusion utilised the shortest amount of time to compute the recognition rate in Euclidean distance. Still, unfortunately, the recognition rate for each intra-feature fusion is the lowest compared to the other distance measures, as shown in Figure 7. On the other hand, the computation time of the LERM distance to calculate the recognition rate is the longest among the other distance measures. However, the recognition rate of the majority of inter-feature fusions achieves superior performance in LERM distance, as illustrated in Figure 7.

Results of fusion integration

The recognition rate for each fusion integration is presented in Table 3. There are five different combinations of fusion integration that have been tested in this section.

Table 3. Recognition result of the fusion integration

Fusion Integration	Recognition Rate (%)				
	Euclidean	**CHOL**	**LD**	**AIRM**	**LERM**
Depth image	80.05	82.94	90.5	90.58	91.03
Max fusion:					
depth image + surface normal (y-direction)	84.57	86.24	90.83	89.84	90.69
depth image + mean curvature	83.7	84.29	90.63	90.36	90.72
surface normal (y-direction) + mean curvature	85.35	86.61	**93.41**	92.83	91.88
surface normal (y-direction) + surface normal (average)	85.35	87.52	93.08	93.08	91.88
surface normal (average) + mean curvature	81.43	82.54	89.48	89.24	90.36
Min fusion:					
depth image + surface normal (y-direction)	68.92	75.05	86.56	85.29	85.7

Fusion Integration	Recognition Rate (%)				
	Euclidean	CHOL	LD	AIRM	LERM
depth image + mean curvature	63.4	71.36	83.81	82.86	83.8
surface normal (y-direction) + mean curvature	84.57	85.14	**92.78**	92.12	92.74
surface normal (y-direction) + surface normal (average)	81.98	84.12	91.76	91.12	91.25
surface normal (average) + mean curvature	83.35	85.44	91.47	91.09	91.19
Max – Min fusion:					
depth image + surface normal (y-direction)	79.49	83.62	88.33	87.09	88.78
depth image + mean curvature	75.67	81.53	86.78	86.41	87.31
surface normal (y-direction) + mean curvature	89.68	89.37	**93.66**	93.35	93.51
surface normal (y-direction) + surface normal (average)	83.28	84.49	90.93	89.99	89.71
surface normal (average) + mean curvature	85.31	85.55	91.85	91.36	92.13
Sum Rule fusion:					
depth image + surface normal (y-direction)	80.16	83.17	91.07	90.72	90.6
depth image + mean curvature	80.96	83.43	90.68	90.77	90.86
surface normal (y-direction) + mean curvature	86.16	86.55	92.91	92.44	93.11
surface normal (y-direction) + surface normal (average)	84.70	85.51	**93.56**	92.84	92.80
surface normal (average) + mean curvature	83.20	84.83	91.22	91.07	91.36

Max fusion is produced by contrasting and obtaining the most outstanding values between the two aspects. The reason for choosing max fusion as one of the fusion methods in this section is its effectiveness in selecting the highest recognition rate among the data which is resistant to alterations and can obtain a specific facial trait. Table 3 illustrates that max fusion achieves the highest score with 93.41% in LD distance when it is utilised on the surface normal (y-direction) and mean curvature.

In addition, min fusion is created by contrasting and taking the lowest values between the two traits. Min fusion is selected in this section as it is simple to employ and is useful in retrieving the minimum score among the data to minimise the false positives. Compared to other fusion techniques, the min fusion method, which combines the mean curvature and the surface normal (y-direction), has the highest score of 92.78 %.

Furthermore, max-min fusion is created by subtracting the max and min feature fusions. Due to the effectiveness of max-min fusion, which merges the advantages of both the max and min fusion, max-min fusion is chosen in this section. The system can maintain reliability and accuracy by using max-min fusion, lowering the likelihood of false positives and increasing the system's resistance to noisy data. Among the different distance measures in Table 3, max-min fusion applied to the surface normal (y-direction) and mean curvature achieved the highest recognition rate, with 93.66% in LD.

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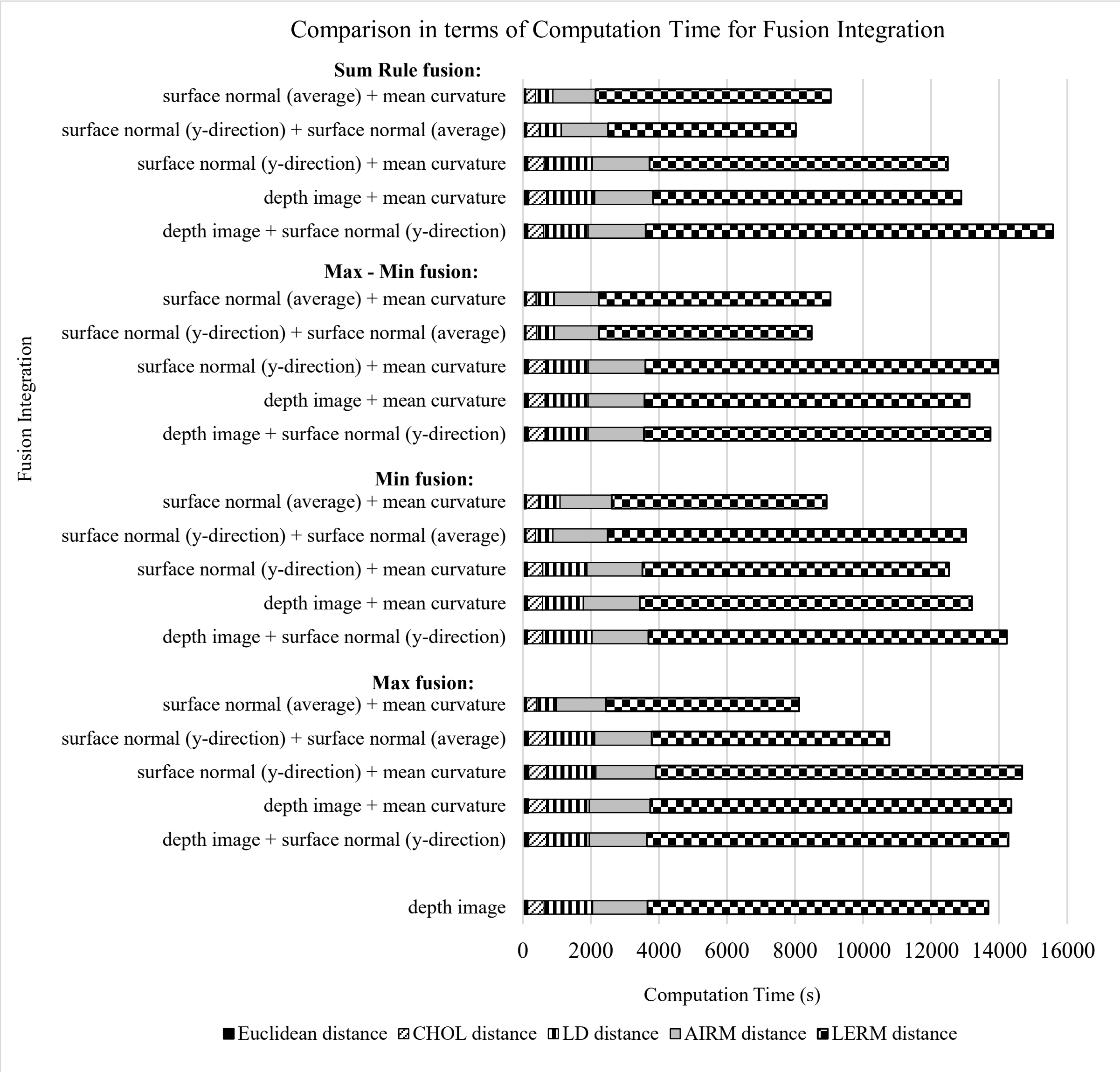

Figure 9. Computation times for fusion integration

Moreover, the sum rule, also referred to as sum fusion, is produced by integrating two distinct characteristics from different sources. The summing of the matching scores from different sources enhances the system's recognition rate, as it contains various facial characteristics from the sources. Due to these advantages, the sum rule is selected in this section. As can be observed from Table 3, contrasted to other distance measures, the sum rule that was implemented to the surface normal (y-direction) along with the surface normal (average) scored the second-best result in the LD distance measure with a score of 93.56%.

In short, it can be concluded that the surface normal (y-direction) + mean curvature, which is the combination of the first and second placed intra-feature fusions, achieves the highest scores in almost every type of fusion method including the max fusion, min fusion and max-min fusion. Besides that, most of the max, min, max-min fusion, and sum rule approaches outperform a single depth image in terms of the recognition rate. By combining two distinct characteristics as a new fusion data (fusion integration), rather than using just one feature, the efficiency of 2.5D face recognition can be improved.

The effectiveness of the fusion integration, including max, min, max-min, and sum rule fusion is shown in Figure 9 via the computation of time in seconds. The total computation time of each distance measure used to evaluate the accuracy rate in fusion integration is almost identical with the inter-feature fusion and the intra-feature fusion times. Figure 9 shows that, for every fusion integration, the recognition rate in Euclidean distance was computed in the least amount of time. However, as shown in Figure 9, the recognition rate for each fusion integration is the poorest contrasted with the other distance metrics. By contrast, the processing period of the LERM distance to compute the recognition rate is the longest among the distance measurements. Nevertheless, the accuracy rate of most of the fusion integrations obtains higher performance in LERM distance.

Comparison with other state-of-the-art methods

Table 4 compares the performance of the state-of-the-art results with the proposed method. From Table 4, our proposed method shows excellent performance compared to the state of the art.

Table 4. Comparison between the state of the art and the proposed method

Authors	Method used	Recognition Rate (%)
Kamencay *et al.* (2014)	CCA-PCA fusion	85%
Chong *et al.* (2014)	Textual image + depth image	80%
Chong *et al.* (2016)	Intra-feature fusion	90.87%
Liu *et al.* (2020)	Echo State Network (ESN) fusion	90%
The proposed method	Fusion integration	93.66%

In this paper, the proposed method is inspired by the work of Chong *et al.* (2014; 2016), which uses various fusion methods to increase the system accuracy rate. With this inspiration, the proposed method recommends using the fusion integration approach, which merges fused data once again to gain more powerful features to improve the system's performance. According to Table 4, the proposed method slightly outperforms the state of the art with an accuracy rate of 93.66%, proving the method's efficiency by using the fusion integration method.

Discussion

Figure 5, Figure 7, and Table 3 show the recognition results for the single depth image, inter-feature fusion, intra-feature fusion, and fusion integration (max fusion, min fusion, max-min fusion, and sum rule fusion). In this study, the max-min fusion used on the surface normal (y-direction) and mean curvature produced the highest accuracy rate of 93.66% compared to the other methods assessed. The depth image is utilised in this experiment as a baseline system for comparing the outcome regarding the feature fusion techniques employed. As can be observed from the experimental results, the accuracy rate of a single depth image is not optimistic, and almost all feature fusion techniques outperform a sole depth image. In summary, this experiment indicates that feature fusion outperforms a sole depth image in terms of recognition performance.

Although almost all feature fusion techniques can improve the performance of the 2.5D face recognition system, each of them still has some limitations. For example, the inter-feature fusion method that combines the features obtained from the 2D and depth data can perform well compared to a sole depth image. However, this feature fusion method that integrates multiple features increases the dimensions and complexity of the feature space, which requires more resources and time for processing.

On the other hand, the other features extracted from the depth image are called intra-feature fusion. Although most of the features derived from the depth image perform better than the single depth image itself, the recognition rate using the derived features is not satisfactory compared to the inter-feature fusion and fusion integration methods. In addition, the fusion integration method, in which the fused data is fused again, achieves the highest recognition rate among the other fusion methods. However, the performance of the fusion integration approach strongly depends on the quality of the features, and features containing noise may affect the effectiveness of the method.

Conclusions

The 2.5D face recognition system with the use of feature fusion approach is proposed in this paper. In the proposed method, the use of more than one type of feature by merging and mixing them up helps to boost the recognition rate of the system. Based on the experimental findings, in comparison to all the fusion techniques, this study proves that the max-min fusion employed on the mean curvature and surface normal (y-direction) has obtained the best accuracy rate at 93.66%. Moreover, nearly all fusion techniques outperform a single depth image in terms of accuracy rate. The computation time of the feature fusion methods relying on several geodesic distance measurements has also been studied in this paper. In the experiment, the best recognition rate was achieved by LD and LERM distance. In future work, more different fusion strategies will be studied and applied to enhance the 2.5D face recognition system.

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A Systematic Literature Review on the Role of Big Data in IoT Security

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Abstract: The Internet of Things (IoT) is an interconnected system of physical objects that are embedded with different sensors (for receiving information), chips, software, and other techniques, which allow connecting and transferring of data to other devices via the Internet without human involvement. Since the number of IoT devices is increasing, large amounts of data are being generated from different sources in different formats. This information needs to be used effectively to gain useful insights for enhancing IoT security. Hence, big data techniques are proposed for managing the data to overcome different issues of IoT. Despite the outstanding achievements in IoT security, a systematic literature review (SLR) on implementing big data for

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securing IoT is lacking. The number of existing related SLRs is limited. Hence, this paper provides a systematic literature review on the use of big data for securing IoT devices. It summarizes the relevant literature produced during the last six years and provides meaningful insights gained by these existing studies. Moreover, it provides a discussion on the sources of IoT big data, the techniques and approaches of big data for securing IoT systems. Current challenges and future research directions are discussed.

Keywords: IoT, Big data, security, big data sources, big data techniques

Introduction

The Internet of Things (IoT) is a network of interconnected devices that send and receive data across the Internet without human involvement. With the increase in the adoption of IoT devices, the amount of generated data has increased exponentially, which has led to the rise in big data (Sachindra & Rajapaksha, 2022). According to a recent report (Hassan, 2022), the number of IoT devices has passed the 14.4 billion mark in 2022, whereas it has been predicted that it will rise up to 27 billion by the year 2027, as shown in Figure 1. With the increase in the number of IoT devices, the challenges, such as security, also increase, since the data generated by these devices is enormous.

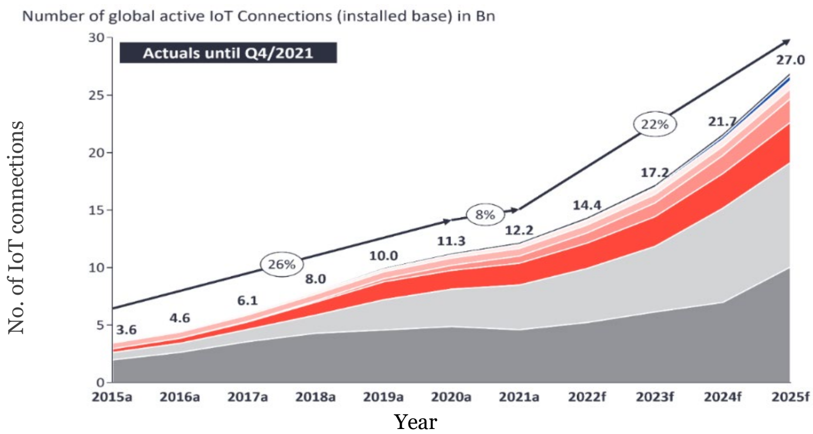

Figure 1. Rate of Increasing IoT devices (Hassan, 2022)

Securing IoT devices and networks is significant as these devices are usually deployed in sensitive environments and are more vulnerable to cyber threats, due to their heterogeneity, resource-constrained nature, low power, lack of standardization (Rao & Deebak, 2022), etc. So, the large and complex data sets produced by IoT devices can offer valuable insights into potential security threats and can help in identifying and preventing cyber-attacks.

Big data in the security of IoT refers to the collection, storage, processing, and analysis of large and complex data sets generated by IoT devices, to secure the devices and the network they are connected to. The data generated by IoT devices associates a wide range of information,

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such as user behaviour (Tedyyana *et al.*, 2022), device configuration, and network traffic, and that information can only be used by big data for gaining insights from it.

Big data for securing IoT includes the use of advanced analytics methods, such as machine learning (Tian, 2022) and artificial intelligence (Paraschiv *et al.*, 2022), for analyzing the large and complex data sets generated by IoT devices. These techniques can be used to detect anomalous behaviour, identify patterns and trends, and predict potential security threats (Pavithra *et al.*, 2019). It can help in improving the overall security of IoT devices and networks by providing real-time monitoring and threat detection, and improving the responsiveness of security protocols by using big data analytics in identifying security vulnerabilities, devices and networks (Hossain *et al.*, 2019).

Moreover, big data plays a vital role in securing the increasing number of IoT devices and networks. By getting insights from large and complex data sets, organizations can be helped in identifying and preventing security threats, improving security protocols, and ensuring the safety and integrity of IoT systems.

However, despite the great research achievements in IoT, in existing studies there is lack of standard and comprehensive work on IoT security using the approaches and techniques of big data. To fill this gap, this systematic literature review (SLR) paper has been written to determine the existing big-data technologies being applied for enhancing the IoT security. The purpose of this study is to review the literature by following a standard approach in reporting on existing big data technologies for IoT security since 2018 up to 2023, specifically focusing on SLRs.

IoT is being used widely in various fields for different purposes. But the security in IoT is a challenging task to solve, and big data is a potential technology to address this problem. Important concepts related to big data and IoT are discussed in the following sub-sections.

IoT security

IoT refers to the interconnected network of physical devices, vehicles, and other objects embedded with software, sensor, and network connectivity. While IoT devices can provide useful benefits, such as enhanced efficiency and convenience, they also pose newer security challenges. IoT security refers to the interventions taken to give protection to IoT devices and the data generated from the issues of cybersecurity threats and communication (Azrour *et al.*, 2021) within the IoT system.

The security risks usually included with IoT devices are many, some of which are:

- **Unauthorized access**: IoT devices could be hacked and be accessed by cyber-attackers, providing access to confidential information or using the device for launching attacks on other systems (Azrour *et al.*, 2021).
- **Data privacy:** IoT devices gather large data amounts, some of which might be personal or sensitive. If this data gets into the wrong place, it can lead to financial fraud, identity theft, or other harmful consequences (Zhang *et al.*, 2022).
- **Malware attacks:** IoT devices could be infected by malware, which can be used for stealing data, causing damage to the device or network, or launching attacks on other systems (Torabi *et al.*, 2021).
- **Lack of security updates**: Some IoT devices lack proper security protocols or get infrequent security updates, or cannot update their firmware, which could make them vulnerable to known security issues.

IoT applications

IoT devices are being used in several applications in different forms, from smart industries to smart cities and wearable technology. While IoT devices provide benefits, they include significant security risks as well, and the nature of these risks varies depending on the particular application of the IoT devices. Some examples of security issues in various IoT applications are discussed in the following sub-sections.

Industrial IoT (IIoT)

Industrial IoT or IIoT refers to the use of IoT devices in industrial applications, such as in manufacturing and energy production. It includes the potential for cyber-attacks on industrial control systems (Taheri *et al.*, 2021) that could result in physical damage or disruption to critical infrastructure. These attacks can be caused by hackers or insider threats. IIoT devices may also be vulnerable to attacks that exploit software vulnerabilities, such as the Mirai botnet attack that targeted IoT devices to launch DDoS attacks (Bhayo *et al.*, 2022).

Smart homes

The simpler form of the IoT ecosystem is in the smart home applications and is used as home security systems, smart thermostats, and control of smart appliances. Security risks in smart homes constitute the potential for unauthorized access to networks of home devices, which could be used for stealing personal information or launching attacks on other systems (Al Mogbil *et al.*, 2020), can be used for tracing one's location, or can enable someone to spy on one's routine and trace the complete routine and one's activities. Smart home devices might also be vulnerable to attacks that exploit software vulnerabilities or weak passwords (Khare & Totaro, 2020). Moreover, there is a risk of data breaches and cyber-attacks that could compromise home security and privacy by stealing and compromising information or IoT devices.

Smart cities

In smart-city applications, IoT is used for services such as traffic management systems, public safety systems, and environmental monitoring. Security risks in smart cities include the potential for cyber-attacks, which disrupt critical infrastructure and cause widespread disruption (Rao & Deebak, 2022). Smart-city devices may also be vulnerable to weak encryption. Moreover, there is a risk of data breaches and cyber-attacks that could compromise public safety and privacy and compromise the departmental works associated with the smart city.

Big Data

Big data refers to the huge volume of data, such as structured, semi-structured, and unstructured data, which is generated and gathered by organizations daily. The term "big data" has become famous in recent years due to the extreme growth in data volumes and the need to process, analyze, and derive insights from this data. According to a report by IDC (Reinsel *et al.*, 2017), the big data volume is predicted to reach up to 175 ZB by the year 2025, as shown in Figure 2.

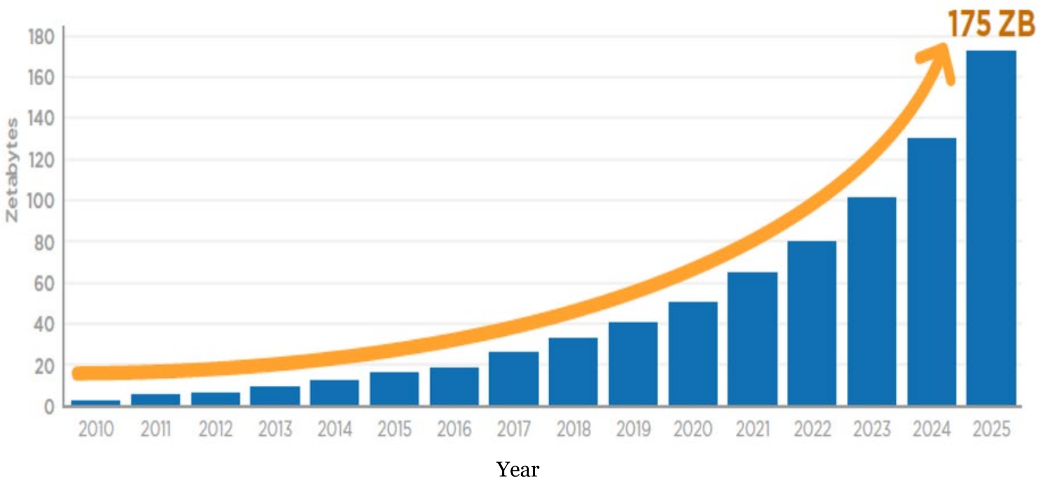

Figure 2. Data growth rate (Reinsel *et al.*, 2017)

Data is considered big data if it has certain characteristics. Big data can have a wide range of characteristics (Islam *et al.*, 2022), among which the five important can be summarized by the "5 Vs" (Figure 3): volume, velocity, variety, veracity, and value, as described in Gutta (2020):

Volume: Big data refers to datasets that are too large and complex for traditional data processing systems to handle.

Velocity: Big data is generated at a very high speed and needs real-time processing to derive meaningful insights from the generated data.

Variety: Big data comes in different formats and structures, including videos, text, images social media data, and machine-generated data from IoT devices and sensors.

Veracity: This refers to the assurance of the data for quality, accuracy, credibility, and integrity, as the data is received from many sources and so its accuracy has to be assured before using it for gaining insights.

Value: Big data has to be of some value when used for insight into a business, so it is the usefulness of the data for making decisions. The value of big data has to be extracted by use of suitable big data analytics methods.

The challenges in handling big data need specialized techniques, tools, and technologies for managing, storing, processing, and analyzing these larger datasets. Big data technologies have been developed to handle the volume, velocity, and variety of big data (Sharma *et al.*, 2022), as well as to offer efficient and cost-effective solutions for managing and processing this data.

Figure 3. Characteristics of big data

One of the important technologies used for big data is distributed computing, which includes breaking down these large datasets into smaller chunks and processing them across multiple servers in parallel. This method allows for better scalability and fast processing of big data. Apache Hadoop (Li & Zhang, 2020) is one of the well-known distributed computing frameworks that is used for big data processing.

Another technique being used for big data is NoSQL databases, which are designed for handling unstructured and semi-structured data, which cannot be handled using traditional relational databases. NoSQL (Kalid *et al.*, 2017) databases are enhanced for horizontal scaling and are able to store and retrieve larger volumes of data.

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Data visualization is another important facet of big data, as it lets businesses gain insights and make informed decisions based on the particular data. Visualization tools like Tableau (Kumar *et al.*, 2022) and BDViewer (Li *et al.*, 2018) allow users for creating interactive charts, graphs, and dashboards for presenting and analyzing data in a meaningful way.

The importance of big data in business cannot be overstated. Big data when used with IoT, can provide many benefits, such as reducing the occurrence of security threats by gaining insights from the user behaviour or IoT devices, identifying patterns of the operations in the IoT ecosystem, and making data-driven decisions. By identifying and detecting abnormal behaviour, it can help in detecting security threats; hence, security issues can be handled or reduced importantly. Besides that, it can also solve the issue of data storage and management.

Research Contributions and Structure

In this study, a systematic literature review is being presented that contains a detailed literature review on the use of big data in IoT for securing IoT ecosystems. The contributions are as follows:

1. Current research status regarding IoT security by using big data techniques;
2. Sources of big data in IoT are identified and discussed;
3. Tools and techniques of big data for providing security solutions to IoT security challenges;
4. The main results of the contribution of research are discussed;
5. Future research directions are identified and discussed.

This paper is organized as follows. First comes a review of the existing pieces of literature. Then follows the research methodology and the research questions. A further section discusses the results of the research questions. Finally, there is a conclusion and an outline of future research directions.

Literature Review

In this section, the existing literature on the scope of big data in IoT is reviewed. The main goal is to identify the use of big data benefits in IoT, which will be undertaken to understand the existing works on the use of big data solutions for IoT applications and to identify the hidden challenges related to it, unrecognized opportunities, and the future research directions. The aim of this systematic literature review paper is to help fellow researchers better understand and implement the concepts of big data in IoT.

To achieve the aim of this study, the existing literature such as systematic reviews, survey papers, and systematic mapping studies related to the field, and published between 2017 and

2023 have been gone through. The summary of the topics and main objectives of each paper is shown in Table 1**.** Out of 9 literature works, only one follows a systematic approach. More recently, in 2023, Bulatova (2023) provides a solution for strategic decision-making about the transportation system in smart cities and it is based on the concept of big data. It is based on an algorithm that uses big data and helps in making decisions for the transportation system. This paper does not follow any systematic process for the research methodology. In 2022, Zhong *et al.* (2022) provided a systematic survey on data mining and big data analysis in IoT, which is mainly focused on highlighting the main architectures of big data and data mining for IoT, the main tools of big data, the challenges of IoT when using big data and data mining, and the purpose for combining big data and IoT. In another survey by Islam *et al.* (2022), a systematic mapping study is provided that mainly concentrates on identifying the privacy attacks in IoT and big data by following a systematic approach. It identifies the main privacy attacks, identifies the measures for overcoming those privacy attacks, and the future research directions in the topic.

In 2021, Hajjaji *et al.* (2021) performed a systematic review of big data and IoT-based applications in smart environments that puts its focus mainly on the challenges of IoT and big data in environmental applications. It discusses the main tools and technologies of big data and IoT in environmental applications as well. This survey does not contribute mainly to future research. Ageed *et al.* (2021) shows the challenges and opportunities of applying big data systems in smart cities and also gives a comparison of different smart cities and big data concepts. Also, it seeks to define criteria for the development of big data applications for innovative services in smart cities. This paper focuses only on one particular application of IoT, the smart city.

Table 1. Existing related literature

Reference	Objectives & topics	Domain	Paper type
Saeed *et al.*, 2023	It discusses IoT and big data-based applications in intelligent ecosystems for identifying challenges and future research directions.	Big data and IoT in intelligent ecosystems	Systematic Review
Bulatova, 2023	It proposes an algorithm for making strategic decisions in smart city transportation systems by using big data.	Smart cities transportation system	Algorithm-based

Reference	Objectives & topics	Domain	Paper type
Zhong *et al.*, 2022	It presents a systematic survey of existing literature on data mining and big data in IoT. It aims at identifying lines of research for future works on the aforementioned topic. Provides summary of the approaches used in IoT-based data mining and big data analysis.	Big data analysis in IoT	Systematic survey
Islam *et al.*, 2022	It highlights the privacy objectives, attacks, and measures to prevent them in IoT and big data. Besides, the classification of attacks is provided.	Big data and IoT	Mapping study
Mohamad Jawad *et al.*, 2022	It is an SLR that discusses the motivations, challenges, and recommendations in smart healthcare.	IoT in healthcare	SLR
Misra *et al.*, 2022	It reviews and shows the use of big data analysis and IoT in food industry for food quality assessment, machinery monitoring.	IoT and big data in food industry	Review
Ageed *et al.*, 2021	It highlights the challenges and opportunities of applying big data systems in smart cities and provides a comparison of different smart cities and big data ideas. Besides, it seeks to define criteria for the development of big data applications for innovative services in smart cities.	Smart city	Survey
Karimi *et al.*, 2021	It reviews the use of big data for enhancing the smart city services and security.	Big data & IoT in smart city	Systematic review
Hajjaji *et al.*, 2021	It presents a systematic review of big data and IoT-based applications in smart environments focusing on the challenges of IoT and big data in environmental applications. Also, it provides the main tools and technologies of big data and IoT in environmental applications.	Smart environments	Systematic Review
Amanullah *et al.*, 2020	It provides a comprehensive survey of securing IoT by detection of security breaches using big data and deep learning.	Big data & deep learning in IoT security	Survey
Farooq *et al.*, 2020	It reviews the use of IoT technologies for addressing different domains of agriculture for improvement of food industry.	IoT in agriculture	SLR
Maswadi *et al.*, 2020	It discusses the systematic review of smart home implementation for elderly people.	Smart home	SLR

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Reference	Objectives & topics	Domain	Paper type
Shah *et al.*, 2019	It shows the growing role of IoT and big data analytics in disaster management applications. By the inquiry of recent studies, review on ubiquitous solutions, categorization of thematic taxonomy proposed, as well a conceptual model on big data analytics and IoT deployment in disaster management is proposed.	Disaster-management	Survey
Florence & Shyamala, 2019	It provides a survey of smart transportation systems in several applications, such as logistics, self-driving cars, traffic prediction, freight transportation, etc.	Smart transportation system	Survey
Al Mamun & Yuce, 2019	It discusses a review of current research & development for sensors and systems, such as wearables devices designed for environmental IoT applications. Provides comparison of existing wearable environment and monitoring systems.	Monitoring environment	Exploratory study
Saha *et al.*, 2018	It has provided a classification of techniques of big data used in IoT applications.	Big data techniques	Survey

From the results of these studies, it is clear that, while some reviews do cover IoT and big data concepts, these studies mainly focus on one specific application of IoT rather than talking about general IoT.

As a result, it is observed that there are still gaps in research to plan and design integrated IoT and big data technologies for IoT security. Therefore, to the best of our knowledge, this work of presenting a systematic literature review on securing IoT by using big data techniques would be the first SLR on the topic.

Methodology

The purpose of the study is to analyze the existing published studies to characterize the use of big data and approaches in IoT security, from the point of view of practitioners and researchers. To fulfill the purpose, the following research questions have been derived (Kitchenham *et al.*, 2009)

1. What is the distribution per publication venue, year, and domain of the published studies related to big data and IoT in securing IoT networks?
2. What are the sources of big data in IoT ecosystems?
3. What technologies and approaches of big data are being used for addressing security issues in IoT?

To achieve this purpose, an SLR has been conducted by using the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)" method (Page *et al.*, 2021). By using this method, the results and methods of systematic reviews can be synthesized in appropriate detail for users to assess the applicability and trustworthiness of the review results.

The search and analysis are discussed through the following review protocol.

Planning

The planning stage of the process consists of the following subsections in which the whole planning stage is described.

Review protocol

The protocol of this study has been designed and is shown in Figure 4. The protocol consists of three phases, which are planning, conducting, and reviewing. Initially, in the planning phase, research questions need to be designed, then the selection of sources and the search strategy is formed, then inclusion and exclusion criteria are performed, and then the quality assessment criteria for selecting papers are chosen. After that, in the conducting phase, primary studies are selected by quality assessment, and the data extraction for the finalized papers is done. At last, in the reviewing phase, the results are formed from a data synthesis of the finalized papers.

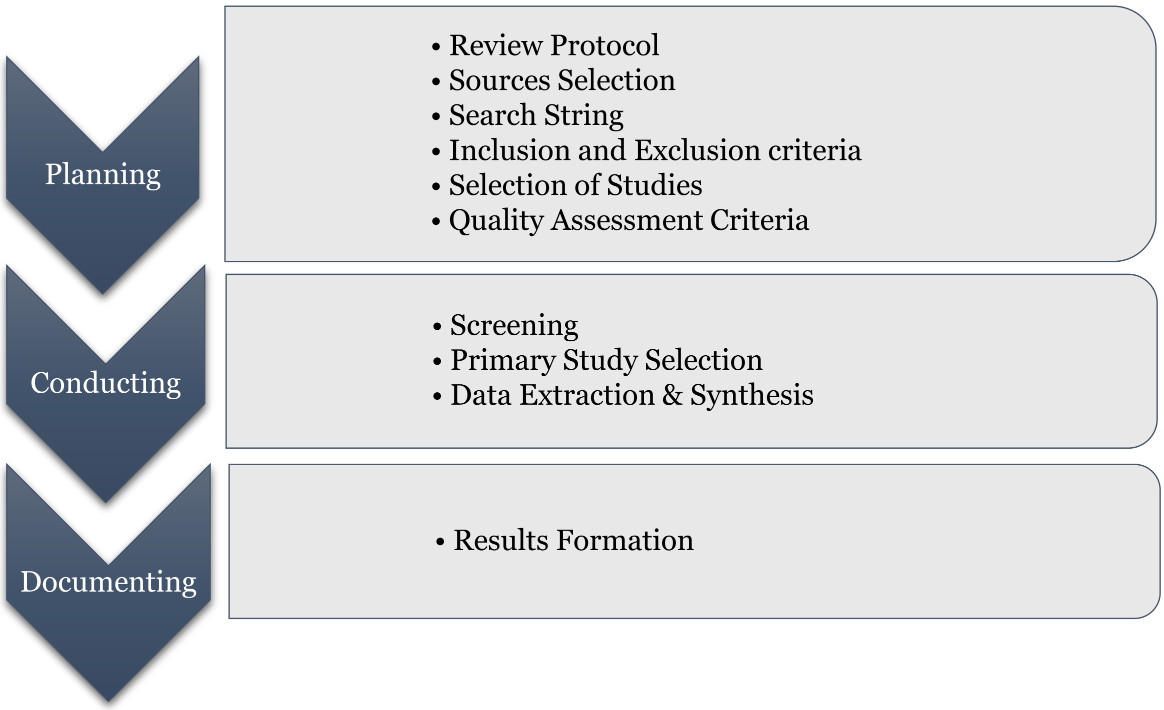

Figure 4. Review protocol

Sources selection

Different online databases have been chosen as search sources. They are IEEE Xplore, SpringerLink, ScienceDirect, Scopus, and ACM digital library. These online sources have been chosen based on their quality, timeliness, availability, and versatility.

Search string

For developing the search string, the keywords are highlighted related to the main idea of the topic of the SLR, i.e., “IoT security” and “big data”. To have an effective search strategy, similar words for the two identified keywords have been produced. Based on that, the search string using specified keywords and Boolean operators (shown in Table 2) has been developed for finding as many studies as possible.

Selection of studies

The studies related to the topic of this study, “big data analytics” and “IoT”, have been searched using the aforementioned digital libraries and have produced a wide range of online published studies from different sources, as shown in Table 2. The selection of studies has been done by applying the inclusion and exclusion criteria shown in Table 3. Based on that, the studies are filtered to get the most relevant and useful ones.

Table 2. Data sources and study selection

Digital Library	String	Studies
IEEE Xplore	((“big data” OR” big data approach” OR “big data techniques”) AND (“IoT security” OR “Internet of things security” OR “security IoT” OR “IoT challenges”))	2232
SpringerLink	((“big data” OR” big data approaches” OR “big data techniques”) AND (“IoT security” OR “Internet of things security” OR “securing IoT” OR “IoT challenges”))	6867
ACM	((“big data” OR “big data techniques”) AND (“IoT security” OR “Internet of things security” OR “IoT challenges”))	1234
ResearchGate	((“big data” OR” big data approaches” OR “big data techniques”) AND (“IoT security” OR “Internet of things security” OR “securing IoT” OR “IoT challenges”))	1678
ScienceDirect	((“big data” OR “big data techniques”) AND (“IoT security” OR “Internet of things security” OR “IoT challenges”))	2547

Inclusion and exclusion criteria

Based on the inclusion and exclusion criteria shown in Table 3, the selected papers from the digital libraries have been screened. By applying the inclusion criteria to selected papers, title and abstract screening is done, at which point it is checked for the published dates of the papers, the topic of the paper, the written language of the paper, and the source of the published paper. There is a need to select papers that are written in the English language and are recently published (after 2019). Similarly, the exclusion criteria have been applied in the title and abstract screening for the dates, topics, and source type of the paper.

Table 3. Inclusion & exclusion criteria

Inclusion Criteria
Studies published between 2017 and 2023
Studies published only in conferences, journals, book chapters
Studies written in English language only
Studies related to big data analytics
Studies related to IoT
Exclusion Criteria
Studies written in other than the English language
Magazines, non-peer-reviewed
Studies written on fields unrelated to our topic
Studies published before 2017

Quality assessment

For filtering the primary studies to the best ones, a quality assessment has been done on the set of 102 papers based on the following 3 questions:

1. Is the motivation for studying IoT and big data mentioned?
2. Is the information given related to big data and IoT?
3. Is a proper methodology followed with results?

Based on the answers of quality assessment conducted on the set of 102 papers, 62 papers have been removed that have not followed the quality assessment criteria. So, at last, 40 papers have been selected for data extraction.

Conducting

In the conducting stage, the primary studies are screened and analyzed as described in the following subsections.

Screening

The studies retrieved and selected from different sources have been screened based on title and abstract, so that only a relevant set of primary papers will be selected for further analysis.

After that, the selected set of primary papers have been screened fully, such that full-text reading has been done so that a set of primary studies can be specified for data synthesis.

Primary study selection

Title and abstract screening and full-text screening has been done on the collected papers for specifying the set of papers for primary studies' collection for data synthesis. Therefore, after the title and abstract screening, out of 7680 papers, 840 papers have been chosen (shown in Figure 5) on which full-text screening is done based on the inclusion and exclusion criteria; and, as a result, 102 primary studies have been identified on which first quality assessment and then data synthesis have been performed.

Table 4. Data extraction

Variable	Description	Research Question
V1	Title	1, 2, 3
V2	Author name	1, 2, 3
V3	Publication year	1
V4	Type of paper	1
V5	Paper methodology	3
V6	Big data approach	3
V7	Purpose of approach	3
V8	Big data sources	2
V9	Type of sources	2
V10	Big data technologies	3

Data extraction & synthesis

For extracting the data from the set of primary studies, a template has been developed as shown in Table 4. Each field of data extraction has a description and a reference to the corresponding research question number. To answer the research questions, the identified primary studies are divided into four facets. Therefore, each variable in the data extraction table is related to answering each research question.

PRISMA flow summary and phases of SLR

A total of 10549 papers have been retrieved from the aforementioned digital libraries. For further selection and filtration of the papers, the PRISMA (shown in Figure 5) method has been followed and the papers are filtered in the following way:

1. In the identification stage, 10549 papers are identified, and then, after duplicates removal, this becomes 7680.
2. In the stage of screening, by doing the title and abstract screening of the papers, 840 papers are selected and the rest of them are removed.
3. At the stage of eligibility, full-text screening has been done and 102 papers been selected for quality assessment. Out of 102 papers, only 40 papers have been finalized as quality papers.

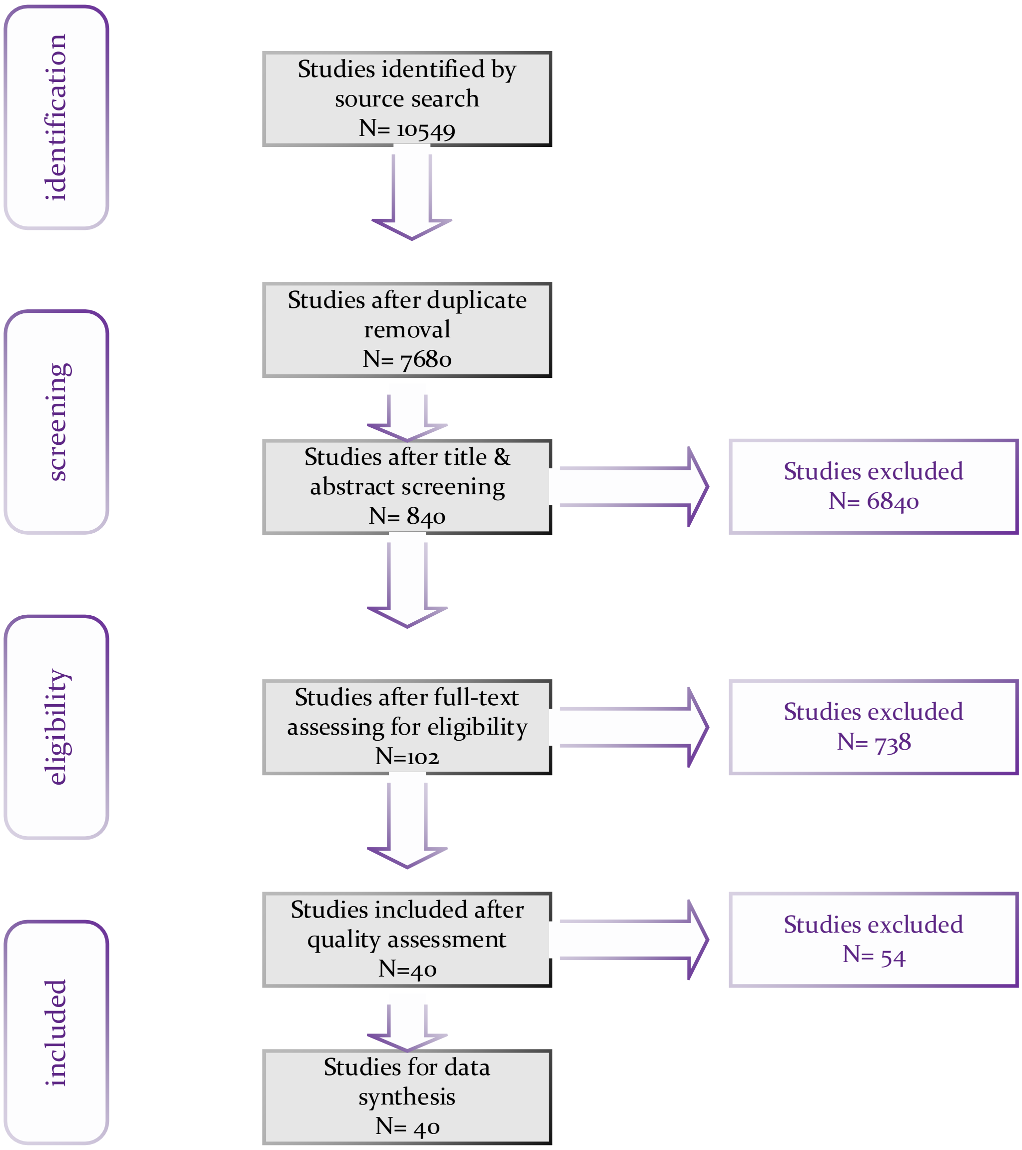

Figure 5. PRISMA flow diagram

Results and Discussion

This is the documenting stage of the SLR process. In this section, the findings are presented based on the analysis of data for each research question mentioned above. Firstly, the demographics of the papers, which have been used in the SLR, are stated. Then, the results of each research question is discussed.

Demographics of studies (RQ1)

The number of published articles on the use of big data in IoT is shown in Figure 6**.** By observing Figure 6, it can be said that the number of published articles is increasing from 2019 onwards. There is 1 article from 2017 and none from 2018. Six articles have been included from 2019 (Hossain *et al.*, 2019; Pavithra *et al.*, 2019; Chui *et al.*, 2019; Florence & Shyamala, 2019; Al Mamun & Yuce, 2019; Shah *et al.*, 2019), whereas the number of articles included from 2019 onwards are more each year, such that 8 articles are from 2020 (Wang *et al.*, 2020; Granat *et al.*, 2020; Li, *et al.*, 2020; Li & Zhang, 2020; Wu *et al.*, 2020; Al Mogbil *et al.*, 2020; Khare & Totaro, 2020; Zhaofeng *et al.*, 2020), 10 articles are from 2021 (Lv *et al.*, 2021; Wan *et al.*, 2021; Azrour *et al.*, 2021; Putra *et al.*, 2021; Ning *et al.*, 2021; Taheri *et al.*, 2021; Torabi *et al.*, 2021; Srinivas *et al.*, 2021; Hajjaji *et al.*, 2021), 12 articles are from 2022 (Tedyyana *et al.*, 2022; Yu *et al.*, 2022; Bhayo *et al.*, 2022; Rao & Deebak, 2022; Sharma *et al.*, 2022; Paraschiv *et al.*, 2022; Zhang *et al.*, 2022; Tian, 2022; Islam *et al.*, 2022; Sachindra & Rajapaksha, 2022; Zhang, Y., 2022; Zhong *et al.*, 2022), and 3 articles from 2023 (Mahmood *et al.*, 2023; Babar *et al.*, 2023; Bulatova, 2023) in the early part of the year. From that, it can be concluded that research on the use of big data in IoT security has gradually increased year by year and is in the stage where it can be said that it is not fully developed or is in its early stages, indicating emerging research.

Figure 6. Rate of publications on big data and IoT

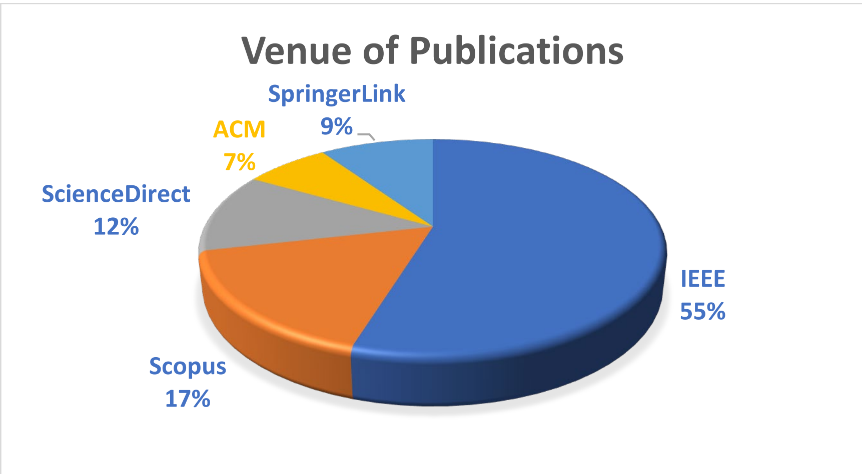

Figure 7. Distribution of venue of publications

Based on the publication venues, the primary papers selected are distributed as shown in Figure 7. It can be concluded from the distribution graph that most of the papers selected are from IEEE Xplore (55%), as Xplore is one of the top digital libraries worldwide. Papers from

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Scopus are (17%), then ScienceDirect (12%), and, finally, from SpringerLink (9%); very few are taken from ACM digital library (7%).

Sources of IoT Big Data (RQ2)

The sources of big data in IoT can be from the following two categories.

Device-generated data

This type of data is generated by low-end devices, sensors used in IoT environments, and machines that are part of the IoT ecosystem. These devices generate data on different aspects such as humidity, temperature, pressure, location, etc. The data generated by these devices is typically time-stamped and is high in volume. This type of data is considered the largest source of data in IoT, making up to 40% of all the sources of IoT data, according to a report by Manyika *et al.* (2015). Wireless sensor networks (WSNs) contain thousands of sensors that gather large amounts of data by monitoring a wide range of areas (Harb *et al.*, 2017). Similarly, a massive amount of data is generated by online transactions done via smart shopping, RFIDs, and many others. There is a huge amount of data being produced by IoT ecosystems but most of the data is not being used or analyzed to make it valuable (Manyika *et al.*, 2015).

User-generated data

This type of data is generated by users of IoT devices in applications like smart home services, wearables, smart parking, smart banking, smart healthcare, etc. This data can consist of information about the user's preferences, behaviour, and location. User-generated data is an important source of big data for the IoT, as most of the data is generated by users. Big data is gained by users of IoT on different platforms such as on social media (Joseph *et al.*, 2017), in the smart office, and human-computer interaction devices. Data is produced in large volume by the user-generated source and this big data can be used to gain insights from it by the use of big data analytics. It also helps in better decision-making, performance boosts, and tightening the security of an organization. One such example can be seen from the research of Joseph *et al.* (2017), where they produced results by performing data analytics on user-generated data of Twitter for discussing trends in IoT. They have used big data tools such as R and NodeXL for data analytics and have gained results like the connection of different user communities, industrial influencers, and top individuals, and security emerging in smart technologies. Similarly, another research work shows a massive amount of user-generated data is being used as a sample for training globally shared models based on federated learning (Wu *et al.*, 2020).

Moreover, different data is generated at different sources like the sensors in accumulating information, users interacting with the IoT devices, and many other data is being generated from IoT devices indirectly. A huge amount of data is generated by the IoT ecosystem (that is, big data) and there are many challenges associated with the huge amount of big data that needs to be addressed by combining big data with IoT technology.

Big Data techniques and approaches for securing IoT (RQ 3)

A large amount of data coming from different sources of IoT, such as sensors, actuators, and other IoT devices, need specific techniques and approaches to make the IoT system secure when handling such big data. For that purpose, different techniques and approaches (Table 5) have been proposed that can make IoT systems more secured by the use of big data concepts.

Table 5. Big data approaches to IoT Security

Reference	Main context	Advantages
Li, 2018	BDViewer	Enables processing of large data sets using web browser based on virtual cloud at back-end
Chui *et al.*, 2019	Monitoring the behaviour of the patient	Reliable and secure
Dhanasekaran *et al.*, 2019	K-mean clustering algorithm based on map-reduce	Optimized data privacy and data storage
Lavanya *et al.*, 2022	Block level security for IoT big data by using cipher security policies	Secured data storage
Tedyyana *et al.*, 2022	Framework for big data is used for providing security to IoT by using SHA-256 encryption	Prevention of external attacks
Yu *et al.*, 2021	Security analysis system for smart home	Detects and prevents security issues in smart home
Srinivas *et al.*, 2021	User Authentication Protocol	Secure communication
Granat *et al.*, 2020	Uses multicriteria approach for event detection in IoT big data analytics	Secured data storage, security, processing
Zhaofeng *et al.*, 2020	Secure Usage Control of IoT big data based on Blockchain-enabled decentralized trust management	Trusted and secure data gathering
Azrour *et al.*, 2021	Enhanced key exchange and authentication protocol	Secured user data exchange across heterogeneous sources
Li *et al.*, 2020	Online distributed security algorithm for IoT	High scalability, better detection, and monitoring of threats
Ning *et al.*, 2021	Mobile Edge Computing blockchain framework	Devices in operation are secured

Most of the time, the security issue exists due to the architecture as, through the architecture of a system or a network, the whole network is communicated among different devices involved and, hence, security can be tightened through this as well. So, for that purpose, a security analysis framework has been introduced by Yu *et al.* (2021), which designs and implements a security analysis system for a smart home for detecting and defending against mining attacks or contactless attacks by incorporating big data into it. For the big data collection in IoT, a secured mechanism has to exist that could allow for secure access to real-time data in IoT; that can be provided by using a three-factor user authentication scheme (Srinivas *et al.*, 2021) known as UAP-BCIoT, based on elliptic-curve cryptography. Similarly, another security framework has been proposed by Tedyyana *et al.* (2022) that uses a SHA-256 encryption method for providing secure data exchange and this prevents external attacks in IoT networks. Lavanya *et al.* (2022) proposes a block-level security by using cipher security policies to secure the data storage in IoT networks. The security issues can be solved to some extent by using such techniques and approaches, but there is also an issue of security and trust for IoT big data management. User authentication can also be secured by a key exchange technique (Azrour *et al.*, 2021) that can provide secure communication in IoT. This issue is solved by a blockchain-based decentralized trust management scheme (Zhaofeng *et al.*, 2020) and also it provides secure data storage, transfer, invoking, and usage.

Moreover, most of the techniques proposed are related to the authentication mechanism and framework. Some are based on encryption techniques as well. It can be said that the researchers are working at fast pace to propose effective solutions for overcoming the security challenges in IoT. Most of them have focused on the architecture of IoT networks, proposing different security frameworks, so that the security issues can be minimized to a certain level in IoT networks. Secure storage of the IoT data is also necessary, as data in storage can be at risk. Secure data exchange is necessary, since, in transit, data can be attacked and compromised. Encryption methods can be used to secure data in process. There is a further focus on securing data coming from heterogenous sources. There is still a need for more research on securing IoT networks by using different techniques of Big Data, as the technology in Big Data is advancing and using advanced technology faces other security issues. Additionally, there is a research gap in providing security solutions for the detection of unreliable data in IoT big data.

Conclusion

Today's world is known as the world of big data, but IoT technology is being further popularized and can lead to a greater explosion of data in the future. The massive IoT networks produce a new type of data called IoT big data. With the advances and progress of IoT networks, security issues arise as well. Existing big data techniques can be used to store and analyze data, so that security issues can be predicted, detected, or minimized. Certain research questions have been formulated to make meaningful conclusions about the identified problems and identify the research gaps.

To make sure of formulating a high-quality report of big data technologies in IoT security, out of 7680 papers, 802 were identified and, after full-text screening, only 40 papers were selected for data synthesis and results formation. An SLR protocol has been followed for identifying

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and formulating results from existing primary studies found in digital libraries. Most of the identified studies were from IEEE Xplore and the number of studies has been increasing from 2018 onwards. The sources of big data in IoT are user-generated and device-generated data. Many big data approaches and techniques are given for securing IoT systems, such as encryption-based techniques, different proposed security frameworks, and authorization and authentication methods.

Current Challenges and Future Research Directions

Information acquisition from IoT data is the main challenge that is posed by big data. Infrastructure development for analyzing IoT is vital. A large number of IoT devices generate a continuous flow of data. The researchers can use these data by using machine learning techniques for creating instruments to extract meaningful information from it. In getting information from an IoT network, scalability and security issues might be faced.

Machine learning and artificial intelligence might be additional directions in future research. Of the large amount of data produced via sensors, a model can be developed to act based on the historic data. Since the raw data and resultant data are both considered as data, big data algorithms should be used for analyzing them. There is space for the improvement of existing algorithms for the process of data analysis to be more secure and efficient, as most of the researchers do not take into consideration the response time and the energy consumption.

Combining machine learning and big data can make it possible to develop a united emergency system that could analyze the given situation and user environment and then take suitable actions based on past cases.

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Incidents and Impacts on Operator Revenue in the Telecommunications Sector

A Multiple Case-Study Approach

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Abstract: This study adopted a multiple case-study approach to investigate incidents, their impacts on performance, and revenues in the telecommunications sector using data from Ghana. The study used open-ended qualitative interviews and document review methods. The study performed a thematic analysis with the Atlas TI software program to analyse the qualitative dataset. The findings resulted in a model dubbed the "Telecommunications Sector Incidents Framework", which reveals that faulty hardware, end-of-system life, cell site congestion, power failure, microwave link failure, fibre failure, and Wi-Fi disconnection are among the incidents prevalent in the telecommunications sector. The framework also reveals that the incidents occur frequently, resulting in an average revenue loss of GH₵2 to 3 million ($182K to $273K) per month. Again, it reveals that employees become demoralized due to a lack of work-life balance, sleepless nights, frustrations, and undue pressure, which affects their productivity levels. With this framework, mobile network operators (MNOs) could get a better understanding of the incidents to keep their occurrences to a manageable level, create an exceptional customer experience by reducing churn, and increase revenues.

Keywords: Incidents, Telecommunications, Impacts, Revenue, Case Study

Introduction

The availability of telecommunication services is a vital concern for society today. People's lives are reliant on their availability, making these services indispensable (Bukhsh *et al.*, 2020). These services are among the key services of every country as they serve and promote other industries to thrive, such as banking, media, advertising, agriculture, health, education, and construction (Nguyen & Tran, 2023; GCT, 2019). When there is a disruption in these services, it in turn leads to decreased quality of life and the potential loss of life or property for

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citizens and subscribers (Bukhsh *et al.*, 2020). These service disruptions are termed incidents, and this is defined by the ISO 20000-1:2011 standard as "an unplanned interruption to a service, a reduction in the quality of a service, or an event that has not yet impacted the service to the customers" (ISO, 2005).

Incidents are considered to be the most difficult challenges in the telecommunications sector. In view of this, failure by mobile network operators (MNOs) to ensure infrastructure resilience and reach makes network reliability a pain point for subscribers (Maya, 2023). A study by Ernst & Young (EY) shows that households constituting 27% in Canada, 26% in France, 24% in Germany, 34% in Italy, 32% in Spain, 22% in Sweden, 27% in the UK, and 33% in the USA frequently experience unreliable broadband connections, resulting from outages, dropped signals, and buffering during streaming (EY, 2023). Bukhsh *et al.* (2020) added that the incidents occur because of system malfunctions, natural disasters, human errors, and attacks that can compromise their availability. Adel (2021) highlights the potential for software vulnerabilities, misconfigurations, outdated systems, and systemic deficiencies in telecommunication services to compromise enterprise assets and cause an initial network failure. Addressing subscribers' complaints effectively based on these incidents is a significant challenge to reducing churn and enhancing security in the telecommunications sector (EY, 2023).

The resulting effect of these incidents is that they can lead to decreased customer satisfaction and loyalty, potentially causing customers to switch providers or demand compensation, resulting in lower revenues and higher churn rates. Similarly, in employees' quest to troubleshoot and restore services, it can cause stress, affecting employees' evening and family time, leading to a decrease in responsible use of technology, negatively impacting organizational performance (Tams *et al.*, 2022; Asentria, 2020).

In the literature review, Bukhsh *et al.* (2020) concluded that there is lack of scientific reports on real-world telecommunication incidents and that this is likely due to confidentiality constraints. Most scientific interest is focused on incidents' method definition (Nawawi & Salin, 2018; Salah *et al.*, 2018; Hu *et al.*, 2017; Zee *et al.*, 2017; Fabian *et al.*, 2015; Carrillo & Chamorro, 2014; Hiran *et al.*, 2013; Luo *et al.*, 2013; Chen & Chou, 2012; Paolino *et al.*, 2011). For instance, a study by Nawawi & Salin (2018) found that employees' carelessness, poor knowledge, and clear intention to act dishonestly contribute to incidents in the telecommunications sector in Malaysia. Also, Carrillo & Chamorro (2014) proposed the adoption of the eSUPERTEL system to gather data on claims, complaints, suggestions, and failures in the provision of telecommunications services. However, as argued by Bukhsh *et al.* (2020), real-world telecommunication incidents and the amount of potential revenue lost by virtue of these incidents are scarcely discussed in the literature.

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As a result, this study sought to establish real-world incidents, their impacts on performance, and revenue, using data from the telecommunications sector in Ghana. The reason is that incidents are more profound and imminent in developing countries due to infrastructure challenges (EY, 2023). This is evidenced in the telecommunications sector in Ghana, as the sector faces various looming challenges in the form of fibre cuts by road contractors and cable theft, resulting in poor quality of service to subscribers. The severity of the incidents made the regulator, the National Communication Authority (NCA) in Ghana, impose a fine to the tune of $6.9 million on the MNOs, namely MTN, Vodafone, and AirtelTigo (Maseko, 2019). While these MNOs and their subscribers experience such incidents, little or no study has been done holistically to establish them and assess their impacts on revenues.

The study used a multiple case-study approach, as it provides great understanding about the differences and similarities between the cases, and its findings are considered strong and reliable (Creswell, 2014; Saunders *et al.*, 2012). The findings of this study could therefore be used as a reference point by policymakers to keep incident occurrences to a manageable level, create an exceptional subscriber experience by reducing churn, and increase revenues in the telecommunications sector. Additionally, the findings would add to the body of knowledge. In view of this, the study sought to answer the following research questions:

1. What are the incidents at the MNOs' workplaces?
2. How do the incidents affect performance?
3. Approximately how much revenue is potentially lost due to the occurrence of these incidents?

The remainder of the study begins with the literature review, followed by the presentation of the methodology, findings, and discussion, and, lastly, the conclusion and recommendation.

Literature Review

The literature review is divided into two sections: the concept of incidents in the telecommunications sector in general and the case of the Ghanaian telecommunications sector.

The concept of incidents in the telecommunication sector in general

An incident is explained as an unplanned and undesired interruption or event that may not result, or only minimally result, in a loss, damage, or injury due to favourable circumstances (Wienen *et al.*, 2017). Similarly, ENISA (European Union Agency for Network and Information Security, 2017) added that an incident is a series of events and failures, often triggered by multiple causes. For example, an incident could be caused by a storm or heavy winds, which may damage power supply infrastructure, resulting in a power cut and later outage as base stations are without power. To explicitly explain the incidents in the telecommunications sector, ISO (2005) said an incident is an unplanned and undesired interruption to a service, a reduction in the quality of service, or an event that has yet to impact the service to the customers.

The literature review on incidents in the telecommunication sector in general reveals that almost all the modern scholars have focused on incident detection and analysis methods (Diop *et al.*, 2023; Koutras *et al.*, 2023; Quek *et al.*, 2023; Tham *et al.*, 2023; Ducca & Margi, 2022; Gibilinda *et al.*, 2022; Adel *et al.*, 2021; Kuchar *et al.*, 2020; Puangnak & Chivapreecha, 2019; Salah *et al.*, 2018; Bloomfield *et al.*, 2017; Fagade *et al.*, 2017; Hu *et al.*, 2017; Nugraha & Legowo, 2017; Choi *et al.*, 2016; Gai *et al.*, 2016; Ordonez *et al.*, 2016; Zaman *et al.*, 2015; Carrillo & Chamorro, 2014; Hiran *et al.*, 2013). For instance, a study by Quek *et al.* (2023) about customer churn prediction proposes a customer churn prediction model using attribute selection analysis and support vector machines. The model improves prediction performance by identifying significant customer data attributes, enabling proactive actions to retain customers, especially with larger database samples.

Also, a study by Koutras *et al.* (2023) about an automated Wi-Fi incident detection attack tool on IEEE 802.11 networks presents a methodology for detecting intrusions from Wi-Fi networks using WiFi-NID. This tool is designed to automate the detection of illegal network scanning attacks at the Wi-Fi access layer. Similarly, a study by Carrillo and Chamorro (2014) about mobile systems for recording incidents in telecommunications in Ecuador proposes the use of eSUPERTEL (Superintendence of Telecommunications) mobile systems for recording incidents in telecommunications services, in order to provide an efficient online customer service channel, contributing to the dissemination of eParticipation and eDemocracy in Ecuador. The aforementioned studies provide valuable methods for incident detection and analysis suggesting that the incidents do occur in the telecommunication sector; however, they do not establish the actual incidents in the real-world telecommunication context and, to a large extent, do not discover the potential revenue loss due to these incidents.

Although a media report by Jacobs (2022) at techtarget.com outlines some common network issues that MNOs face, namely: VLAN and VPN problems; exhausted IP addresses; duplicate and static IP addresses; slow DNS lookups; excessive CPU usage; physical connectivity issues; weak Wi-Fi signals; and slow networks. For instance, he defines excessive CPU usage as whenever a great quantity of system resources, such as CPU, memory, or disk space, are utilized. But there is no scientific study found in the literature, to the best of the researcher's knowledge, validating these suggested incidents.

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Moreover, with respect to factors that bring about incidents in the telecommunications sector, Maya (2023) explains that MNOs face challenges in sustaining infrastructure to satisfy customer demand, intensified by soaring data usage, the digital divide, and the affordability of services, affecting calls and infrastructure. Additionally, ENISA (2017) classified factors that cause incidents into four main areas: system failures; human errors; malicious actions; and natural phenomena. However, within the context of this study, malicious actions are conceptualised as infrastructure incidents, as illustrated in Figure 1.

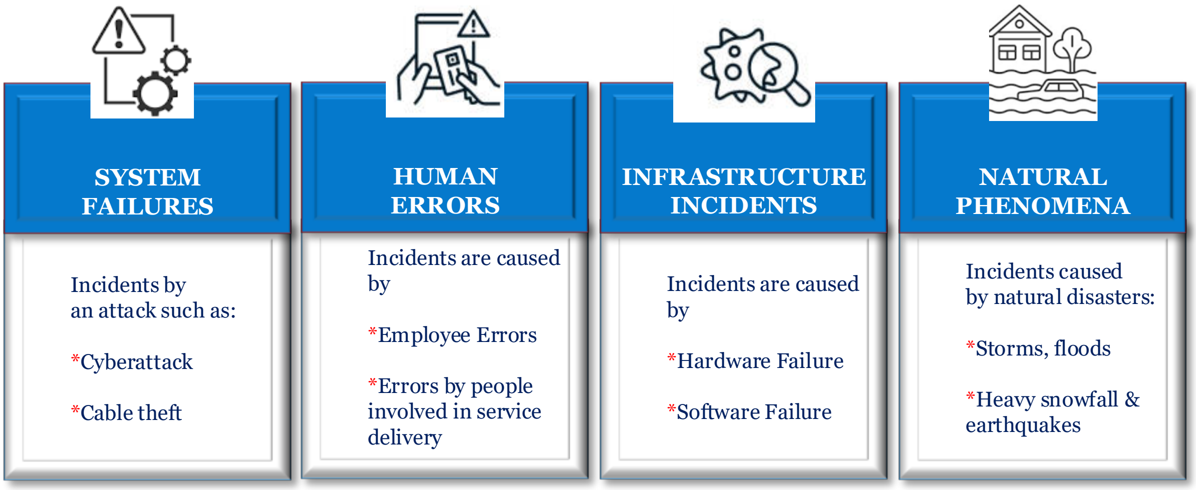

Figure 1: Incidents causal factors classifications (Source: Researcher's own construct based on ENISA classifications)

From the above discussion, it is evident that little has been done to establish the incidents in the real-world telecommunication context, their impact on MNO performance, and, to a large extent, to discover the potential revenue loss due to these incidents; hence, the relevance of this study.

The case of the Ghanaian telecommunications sector

The Ghanaian telecommunications sector is one of the strongest and most competitive in West Africa. This sector, as of January 2023, has 39,812,171 mobile voice subscriptions, constituting 125% of mobile voice penetration, and 22,756,215 total data subscriptions, constituting 72% of mobile data penetration. This sector contributed 22.8% to Ghanaian GDP in 2022 (Ghana Chamber of Telecommunications, 2023; GCB Strategic and Research Dept, 2023).

Unfortunately, after several iterations of searching through databases that contain publications for major journals and conference proceedings, namely Scopus, IEEE Explorer, Springer, and ScienceDirect, with a search string "Telecommunication AND Incident AND Ghana AND (Disruptions OR service downtimes)", all the incidents returned results did not relate to the Ghanaian telecommunications sector. This, therefore, suggests that there is a lack of scientific research on real telecommunications incidents and the corresponding revenues

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lost from the perspective of MNOs, which could have been realized to enhance the sector's contribution to economic development through taxes and infrastructure investments.

Table 1. Fines for MNOs by the Telecommunications Regulator in Ghana

Source	Title	Reasons	MNO	Amount Fined	Date
NCA.org.gh	NCA sanctions MTN for failing to comply with directives on the network challenges	Subscriber challenges with billing inaccuracies regarding the purchase of their telecommunications service bundles.	MTN	**GH₵110,000 ($19,298)**	2019
NCA.org.gh	Telcos sanctioned GH₵34M for failing quality of service tests.	MNOs were unable to meet their license key performance indicators (KPIs) in some district capitals with regards to QoS obligations for coverage, data, voice, and speech quality.	AirtelTigo	**GH₵11,635,000 ($2.36million)**	2018
			Glo	**GH₵4,460,000 ($1.84 million)**	
			MTN	**GH₵9,080,000 ($1.79 million)**	
			Vodafone	**GH₵8,890,000 ($906,682)**	
Venturesafrica.com	Ghana regulator fines mobile operators $461,000.	For defaulting on call congestion and call setup time obligations in three regions.	MTN	**GH₵350,000 ($170,000)**	2013
			Tigo	**GH₵250,000 ($125,000)**	
			Expresso	**GH₵200,000 ($100,000)**	
			Glo	**GH₵200,000 ($100,000)**	
			Airtel	**GH₵50,000 ($25,000)**	
Modernghana.com	The Chamber of Telecommunications reacts to NCA penalties.	Poor service.	MTN, Vodafone, Tigo, Airtel and Expresso	**GH₵1.2million ($300,000)**	2011

NB: **Expresso** has ceased trading**; Tigo, Glo** and **Airtel** have been merged and are now called **AirtelTigo.**

In the absence of scientific research, this study relies so much on some media and regulatory reports about some purported incidents in the sector. A report by the regulator, the National Communications Authority (NCA), in Ghana indicates that it performs telecommunications quality of services (QoS) tests on a quarterly basis, such as obligations for coverage, data, voice, and speech quality (NCA, 2023). When the incidents are beyond the measuring metrics, then it imposes a fine on the perpetrator MNO. For instance, as illustrated in Table 1, in 2019, NCA sanctioned MTN to the tune of GH₵110,000 ($19,298) for failing to comply with directives on subscribers' experience about billing inaccuracies regarding the purchase of their telecommunications service bundles (NCA, 2019). Additionally, NCA fined all the MNOs GH₵34 million ($6.8 million) in 2018; $461,000 in 2013; and GH₵1.2 million ($300,000) in 2011; for failing quality of service tests (NCA, 2018; venturesafrica.com, 2013;

moderngħana.com, 2011). However, neither the regulator nor the reporters indicated the factors that accounted for the service disruptions by the MNOs.

Conversely, there is a report by the Ghana Commercial Bank Strategy and Research Department (2023) about the telecommunications sector that suggests that factors such as the destruction of telecom equipment through construction, a lack of proper infrastructure, an increase in competition, and theft may pose a risk of incidents for consideration by the MNOs in Ghana. Similarly, a report by Maseko (2019) at itnews.com indicates that subscribers experienced various degrees of network disruptions from their mobile network operators in Ghana, which were purported to have come as a result of fibre cuts by road contractors and cable theft. But there is no scientific study based on the literature search results that validates such claims. Therefore, the study seeks to explore the network incidents in this sector and their impact on performance and revenues.

Methodology

This section presents the methodology for the empirical research conducted in this study, as illustrated in Figure 2.

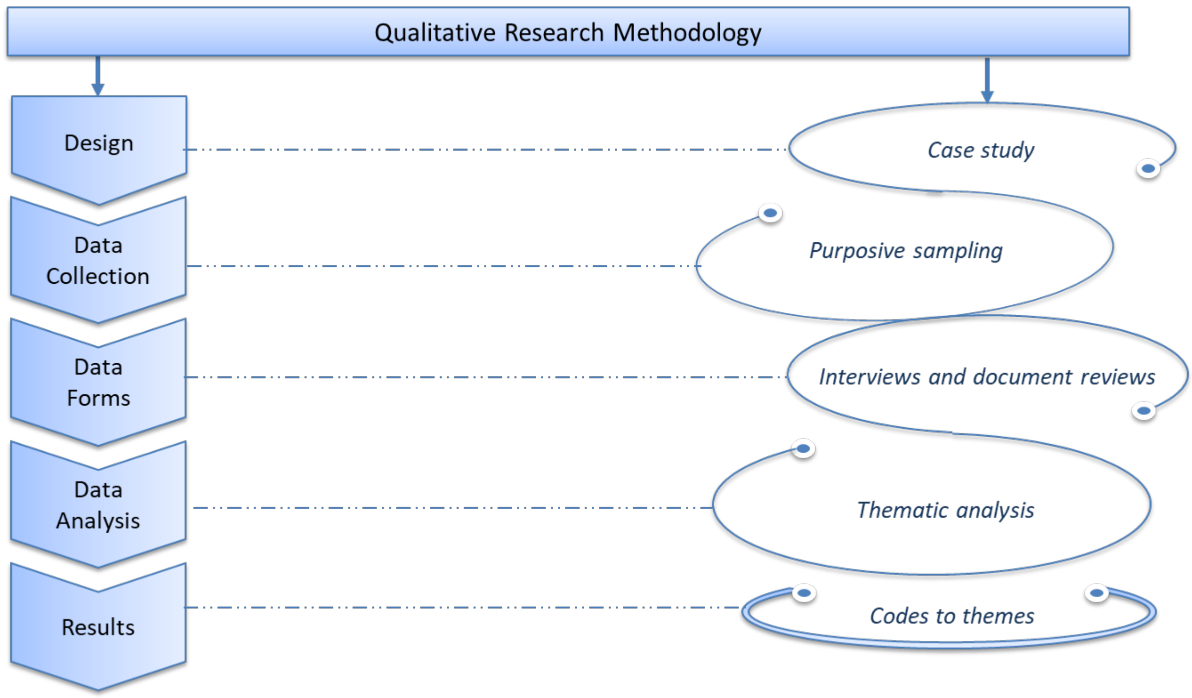

Figure 2. Qualitative research methodological model (Source: Researcher's own construct)

From Figure 2, the study adopted a case study, specifically a multiple-case study, approach, as it offers the opportunity to gain an in-depth understanding of the issues, by identifying common patterns, relationships, and differences between the cases, and the findings are considered strong and reliable (Creswell & Poth, 2018; Yin, 2018; Creswell, 2014; Baxter & Jack, 2008). Therefore, the study chose this research design with the aim of gaining a

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comprehensive understanding and providing new insights into the incidents, their impacts on performance, and revenues in the telecommunications sector using data from Ghana.

Sampling and data collection procedure

The study used all three MNOs in Ghana, namely, MTN, Vodafone, and AirtelTigo (AT). Each MNO constitutes a case, and all three consist of multiple cases within the bounded system, as explained by Creswell & Poth (2018). Within each operator, the study selected six employees through purposive sampling, as it is used to select respondents who are most likely to provide relevant and useful information (Robinson, 2014; Kelly, 2010).

Table 2. Demographic profile of participants

MNO Code	Participant's Code	Gender	Position	Years with MNO
#A	A1	Male	Product Manager (data)	2.8 years
	A2	Male	IT systems Engineer	4.4 years
	A3	Male	Revenue Performance Analyst	8 years
	A4	Male	Head, Performance and Planning	8 years
	A5	Female	Network Engineer (Service Quality)	3.5 years
	A6	Female	Business Intelligent Analyst	5 years
#B	B1	Female	Head, Usage and Retention	10 years
	B2	Male	Sales Incentive Manager	8 years
	B3	Female	Network Engineer	3 years
	B4	Female	Data Specialist	5 years
	B5	Male	IT systems Engineer	4 years
	B6	Female	Business Intelligent Analyst	5years
#C	C1	Male	Head, Direct Sales	3.4 years
	C2	Male	Revenue Assurance Manager	8 years
	C3	Female	Network Quality Engineer	3.6 year
	C4	Male	Head, Product & Innovation	8 years
	C5	Male	Sales Supervisor	5 years
	C6	Female	IT systems Engineer	6 years

Within each case, as presented in Table 2, the study selected three employees from the network and IT departments, whose functional roles are network quality engineer, IT systems engineer, and business intelligence analyst. These employees manage the network infrastructure, systems and platforms, and the intent was to understand the incidents from the technical point of view. Additionally, the study selected the other three within the commercial functions, namely, product management, sales, and revenue assurance, with the aim of obtaining information about the revenue impacts from these incidents. These selected employees were widely recommended within their respective operators based on their levels of experience in the subject matter, with a minimum of 2.8 to 10 years of experience in their roles, as shown in Table 2.

In the data collection phase, the study used open-ended interviews via a telephone interview method and document reviews, specifically MNO incidents posted on Facebook, as recommended by Yin (2018). The study used the telephone interview method because of its obvious benefits of cost effectiveness and time efficiency (Taylor, 2002; Gibson & Cohen, 2003). The intent of the open-ended interviews was to delve into the subject matter and probe it to greater depth while also allowing for free expression of thoughts by the participants (Chenail, 2011). The interviews were carried out between the hours of 12 p.m. and 2 p.m., as recommended by the participants as their most convenient times.

Data analysis

The study used thematic analysis to analyse the qualitative dataset. In view of this, the study used Atlas ti. to create quotations after data familiarization, assign codes, and develop themes, as using such software is a faster and more efficient way of storing and locating qualitative data (Creswell, 2014). The study upheld ethical considerations by providing the MNOs and the participants with pseudonymized codes **#A** to **#C** and **A1-A6** to **C1-C6,** respectively, to protect their identities, as presented in Table 2. The study used ideas from concept mapping and innovation concepts by Miles *et al.* (2014) and Novak & Cañas (2006), respectively, to develop figures and models for illustrating the findings.

Presentation of Findings

As a preamble to the interview findings, the study sought to establish the occurrence of incidents by reviewing the MNO communication posts on Facebook from September to August 2023. The complete findings of the reviews are presented in Appendix 1 and the summary is shown in Table 3. It was revealed that incidents with minor service quality impacts are communicated through short message service (SMS) to subscribers, and the major impacts are posted on social media in addition to SMS. The study established that incidents are inevitable in the telecommunications sector. From the review, it suggests that Vodafone experiences more incidents than its counterparts, MTN and AirtelTigo, in Ghana.

Table 3. MNO incident posts on Facebook

MNO	Incident Posts on Facebook, 2023		Total Posts
	September	August	
Vodafone	4	3	7
MTN	3	1	4
AirtelTigo (AT)	1	3	4

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The subsequent sections present the findings from the interviews. In view of this, the key elements found in the participant narratives were mapped to illustrate the differences and similarities across the cases, and the themes borne out of this exercise are discussed accordingly.

The Incidents in the Telecommunications Sector

Table 4. The incidents in the telecommunications sector

Sub-Codes	Categories	Themes	Aggregated Themes
Faulty hardware	Hardware Failure	**Network failure**	**Incidents in the Telecom Sector**
Hardware failure			
End of life systems			
Cell site (2G, 3G, LTE) outages			
Cell site congestion			
Power failure	Systems Connectivity Failure		
Microwave link failure			
Fibre failure			
Wi-Fi disconnections			
Loss of connectivity to OSS			
Fibre cuts by road construction	Human Errors		
Cell site outage due to stolen batteries			
Breaks in optical fibre			
Outages due to heavy wind & rainfall	Disaster		
Fibre destruction due to erosion			
Cell sites' downtimes by flooding			
Unable to make calls	Service unavailability	**Service failure**	
Inability to browse Internet			
No Internet availability			
Poor coverage			
Network reception in emergencies			
Inability to access shortcodes	Service inaccessibility		
USSD codes fluctuation			
Mobile money disruptions			
Unstable data connectivity	Poor service quality		
Slow data speeds			
Call drops			
Poor voice clarity			
Less severe	Severity	**Incident risk assessment**	**Incident risk and resolution assessment**
Severe			
Very severe			
Often	Frequency		
Sometimes			
Always			
Minute(s) (10 to 50)	Resolution time	**Incident resolution assessment**	
Hour(s) (1 to 4)			
Day(s) (1 to 5 days)			

This section presents incidents in the telecommunications sector using data from mobile network operators (MNOs) in Ghana. The codes created from the participants' narratives are

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mapped across to generate categories, themes, and aggregated themes as comprehensively presented in Appendix 2. Table 4 provides a summary of findings on the incidents in the telecommunications sector.

Network failure

This is the most prominent theme in the dataset, as the network is the architecture and lifeblood of telecommunication services, and its failure is of great concern to the survival of the MNOs. The network failure, as presented in Table 4, is characterized by:

- Hardware failure refers to the malfunction of hardware, end of system life, congestion at the cell site, and outages at the 2G, 3G, and LTE frequencies, as stated by A5, B3, B6, and C3, and C6 in cases **#A**, **#B**, and **#C,** respectively (see Table 4 and Appendix 2). For instance, A5 stated that:

  "Outages caused by microwave link failure, multiple fibre failures due to road construction, downtime due to faulty NPU 1C, and cell site outages caused by power or hardware failure" [**#A**, Network Engineer, Service Quality].

- System connectivity failure occurs due to power failure, microwave link failure, fibre failure, Wi-Fi disconnection, or loss of connectivity to OSS (Operations Support System), as found in all the cases and stated by A2, A3, B3, B6, C3, and C6. But this is strongly emphasised by C3:

  "Power failure, loss of connectivity to OSS, site is down due to faulty hardware, fibre cut and links failure, cell site outages due to stolen batteries, end of life systems causing service interruptions" [**#C**, Network Quality Engineer].

- Human errors, such as theft of batteries, road construction cutting of fibre, and optical fibre breaks, can cause cell-site outages, as shown in Table 4. These incidents are predominantly found in cases **#A** and **#B**, as alluded to by A2:

  "Fibre cuts are accidental breaks in an optical fibre, typically due to new construction in the area. Outages caused by power failure and microwave link failure" [**#A**, IT systems engineer].

- Disaster incidents can result in outages due to rain, fibre destruction due to erosion, and cell site downtimes due to flooding. This is explained by B4 as:

  "Challenges in accessing network services include outages across major cities due to heavy rain falls, fibre destruction due to erosion, and cell site flooding" [**#B**, IT systems engineer].

http://doi.org/10.18080/jtde.v12n1.852

Service failure

From Table 4 and Appendix 2, service failure is another important theme that emerged across the cases, and that reflects how the MNOs fail to fulfill their obligations to render services to their customers. The incidents are put into three main categories:

- Service unavailability includes the inability to make calls and browse the Internet, a lack of Internet availability, and poor coverage across all cases. For instance, B6 stated that "no Internet availability means that when Wi-Fi disconnects, dumps and cubes can't be accessed until the issue has been resolved" [**#B**, Business Intelligence Analyst].

- Service inaccessibility involves issues with shortcode access, fluctuating USSD codes, and disruptions in mobile money services, as alluded to by A4 and C4, respectively:

  "Call drops; unable to make calls to all networks" [**#A**, Head, Performance, and Planning].

  "USSD codes fluctuate, making it impossible to access network services. Slow data speeds" [**#C**, Head, Product and Innovation].

- Poor service quality consists of unstable data connectivity, slow data speeds, poor voice clarity, and call drops, as noted by A3, B1, B5, C1, C4, and C5. For example, B1 emphasized that:

  "Total network downtime and slowness in browsing; 2G site downtimes making calls difficult; poor voice and data coverage; intermittent drop in Internet bandwidth" [**#B**, Head Usage, and Retention].

Incident risk and resolution assessment

From the incidents in the telecommunications sector discussed above, the study assessed the risk associated with the incidents and their resolution time across the cases as shown in Table 4 and Appendix 2. The findings across the cases revealed that the impact of these incidents is *very severe,* and their frequency of occurrence is also *very high*. The study found across the cases that it takes, on average, *one to four hours* for the incidents to be resolved for service restoration.

The impacts of the incidents on employees and MNOs performance

This section discusses the impact of the incidents on employees and MNO performance in the telecommunications sector using data from Ghana. Appendix 3 displays key codes that were mapped across the cases to identify their differences, similarities, and themes produced from the analysis. Table 5 presents a summary of findings on the impact of the incidents on employees and MNO performance.

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Table 5. The incidents' impact on MNOs performance

Sub-Codes	Categories	Themes	Aggregated Themes
Employees have sleepless night	Employee personal life impact	**Employee morale impact**	**The incidents impact employees' performance**
Employees' family life impact			
Employee become frustrated	Employee work balance impact		
Employees become pressured & stressed			
Affect KPI achievement	Employee target achievement impact	**Employee performance impact**	
Miss targets			
Delay in performance reporting			
Slow down work rate	Employee productivity impact		
Employee become idle			
Customer churn	Customer base impact	**MNO performance impact**	**The incidents impact MNO's performance**
Difficult to acquire subscriber			
Loss of revenue	Financial impact		
Impact new sales revenue			
Affect company growth	Target achievement impact		
Impact company's monthly target			
Unrealised company's target			
Impact company performance reporting	Performance visibility impact		
Impact decision-making process			
Service unavailability	Service provision impact		
Service inaccessibility			
Customers become agitated and furious	Customer satisfaction impact	**MNO image impact**	
Customer dissatisfaction			
Regulatory sanctions (fines)	Brand image impact		
Media bashing			
Erode brand image			
Communication challenges			

The impacts of the incidents on employees' performance

In assessing the incident impacts on employees, the findings revealed that "employee morale impact" and "employee performance impact" are themes that emerged from the data analysis as presented in Table 5 and Appendix 3.

- The impact on employee morale is broadly categorized into two main areas: personal life impact and work balance impact. The former relates to employees' sleepless nights and poor family life, as explained by C6: "troubleshoot and restore services put a lot of pressure on us and become stressful, affecting our family life and also impacting our KPIs" [**#C**, IT Systems Engineer]. The latter is a combination of employee frustration, pressure, and stress, as stated by B4, B5, B6, C2, C3, and C6, respectively. For instance, B5 passionately emphasized that:

"Since all my work responsibilities are dependent on the Internet, such disruptions affect my KPIs, especially active data users and data revenues. Dealing with these interruptions can be frustrating and stressful. It can disrupt my workflow, cause annoyance, and impact my overall job satisfaction" [**#B**, Data Specialist].

- The impact of employee performance is seen in missing targets, resulting in an inability to achieve their KPIs, as well as a slowing work rate and becoming idle. These occur across the cases, as stated by A4 as "slows done work rate", B6 as "it becomes frustrating because you become idle and cannot do anything", and C1 as "it really affects my ability to meet my KPIs".

The impacts of the incidents on MNO's performance

From Table 5, the findings on the incident impact on MNO performance revealed two main themes, namely:

- MNO performance impact: this consists of, first, *customer base* and *financial impact*, where, across all the cases, it was found that, during the incidents, customers churn out of the network, and it also becomes difficult to acquire new subscribers, resulting in a huge revenue loss, as stated by A4 as "low acquisition of customers and revenue loss" [**#A**, Head, Performance and Planning], and B2 as "customer acquisition and new sales revenues are mostly impacted, affecting the company's monthly target" [**#B**, Sales Incentive Manager]. Second, *service provision* and *customer impact*, where it was revealed that the incidents make customers dissatisfied with the inaccessibility, unavailability, and poor quality of services, as alluded to by A2:

  "Service availability and accessibility by customers are hugely impacted; customers become dissatisfied, and it may attract fines from the regulator" [**#A**, IT systems engineer].

- MNO image impact relates to customer satisfaction and brand image impact. The findings revealed that the incidents make customers agitated and furious, resulting in customer dissatisfaction, as stated by A1 as "customers become agitated and furious" [**#A**, Product Manager]. Similarly, the MNOs receive public criticism and bashing from the media houses, making incident communication with customers a challenge, as stated by B4 as "the incidents generate public outcry that will affect the company's operations" [**#B**, IT systems engineer]. This, in large extent, brings about the regulatory sanctions, and that tarnishes and erodes the image of the MNOs, as affirmed by C6 as "the regulator will sanction the company with a huge fine, which will erode the company's image" [**#C**, IT systems engineer].

The potential revenue loss and measures to minimise incident occurrence

This section presents the potential revenue loss due to occurrences of incidents and the measures required to minimise their occurrence in the telecommunications sector, using data from Ghana. Appendix 4 presents the complete findings regarding the key codes that were mapped across the cases to identify their differences, similarities, and themes produced from the analysis. Additionally, Table 6 displays a summary of findings on the potential revenue loss due to the occurrence of incidents and the measures required to minimise their occurrences.

Table 6. The revenue loss and measures to minimise incidents' occurrence

Sub-Codes	Categories	Themes	Aggregated Themes
Unable to disclose	Hesitation & lack of information	**Revenue Lost**	**The amount of revenue lost due to the incidents' occurrence**
It depends on the degree of occurrence			
Average GHȻ 100K loss of revenue daily	Loss of revenue disclosure		
An average of GHȻ 2 to 3 million, Month-on-Month (MoM)			
Approximately, GHȻ 1 to 2 million, MoM			
Adequate infrastructure investment	Network infrastructure investment	**Network Infrastructure Investment & System Optimization**	**Measures to minimise incidents' occurrence and impact on performance**
Investment for system upgrade and maintenance			
Leveraging aerial cabling instead of underground	Network infrastructure rollout strategy		
High-end radios as redundancy			
Utilise multiple carriers			
Well-maintained network infrastructure	System Optimization strategy		
Regular hardware system upgrades			
Contingency plans & stable platforms			
Urgent turnaround time for resolution	Effective incident resolution plan	**Effective Incident Management**	
Swift customer communication			
Employee training on disruptions			
Ensure backup equipment availability	System backup plan		
Ensure backup connectivity options			

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The potential revenue loss due to the incidents' occurrence

The findings revealed that the incidents have huge revenue impacts. Although some participants hesitated to reveal the amount of revenue lost amidst the incident, due to their sensitive nature and lack of information based on their roles, as stated by A4, B3, and C2, respectively:

> "I may not be able to disclose this information. Also, it is totally dependent on how long it takes for it to be resolved. It's not one size fits all" [#**A**, Head, Performance and Planning].
>
> "I can't really tell the amount except for the product and revenue assurance units" [#**B**, Network Engineer].
>
> "I cannot reveal that, but it is in millions" [#**C**, Revenue Assurance Manager].

However, the commercial-related employees indicated that such incidents cause MNOs to lose an average of GHc2 to 3 million, month-on-month (MoM). This is explained by C4, A1, and B2:

> "It is approximately GH₵ 2.5 million in revenue loss on a monthly basis" [#**C**, Head, Product & Innovation].
>
> "An average of GH₵ 2 to 3 million in revenue loss on a MoM basis" [#**A**, Product Manager].
>
> "It is about more than a million new sales revenue within the month of occurrence" [#**B**, Sales Incentive Manager].

The measures required to minimise incidents' occurrence

From Table 6, the findings revealed two main categories of measures required to minimize the occurrence of incidents and their impacts on performance. These measures are:

- Network infrastructure investment and system optimization: this measure is to ensure that MNOs adequately invest in the network infrastructure and systems upgrades, as indicated by A2 as "adequate investment in the company's infrastructure" [#**A**, IT systems engineer], and B4 as "capital injection for upgrades of systems and maintenance" [#**B**, IT systems engineer]. Also, MNOs should adopt a different network infrastructure rollout strategy where, instead of laying fibre underground to be destroyed by road construction, they leverage aerial cabling, ensure high-end radios as redundancy, and utilize multiple carriers, as clearly explained by A5:

  > "The use of high-end radios as redundancy instead of cables. Deploying a lot of redundancies in the network. Leveraging over-the-top cabling technology instead of underground" [#**A**, Network Engineer, Service Quality].

  Lastly, MNOs should implement a system optimization strategy, ensuring well-maintained network infrastructure, regular hardware upgrades, and platform stabilization with a contingency plan. This is explained by B2 as "having stable

http://doi.org/10.18080/jtde.v12n1.852

platforms" [**#B**, Sales Incentive Manager] and C6 as "I believe regular hardware and system upgrades can help curtail most of these incidents" [**#C**, IT systems engineer].

- Effective incident management: the findings revealed that employees should be well trained on disruptions, and, amidst incidents, MNOs should ensure swift communication with their customers and manage their expectations by ensuring an urgent turnaround time for resolution. These are explained by B5, A1, and C4, as follows:

  "Educating employees on how to maximize network connectivity and use alternative methods during interruptions" [**#B**, Data Specialist].

  "Swift communication of downtime and urgent turnaround time for resolution" [**A1**, Product Manager].

  "When they occur, a fast response rate to solve the issue and restore services can go a long way toward mitigating the negative effect on the company's performance" [**#C**, Head, Product and Innovation].

Discussion

The findings, as broadly presented above, have been summarised and illustrated in Figure 3, entitled "*Telecommunication Sector Incidents Framework*", using the innovation concept by Miles *et al.* (2014).

In answering question one of the study — What are the incidents in the telecommunications sector? — Bukhsh *et al.* (2020), after systematically reviewing the literature on incidents, concluded that there is a lack of scientific reports on real-world telecommunication incidents, which is likely due to confidentiality constraints. Therefore, the present findings would serve as real-world telecommunication incidents and validate the claims made in the media reports. In view of this, Figure 3 postulates that, broadly, incidents in the telecommunications sector are characterized by network failures and service failures, as briefly elucidated therein.

Network failure is of great concern to the survival of MNOs, as mobile networks are crucial for telecommunication services. The incidents constitute hardware failures where the network becomes congested due to heavy traffic, hardware becomes faulty, and systems are at the end of their lives. Again, system connectivity failures come from power failure, microwave link failure, and fibre failure; also, human errors, such as road construction resulting in fibre cuts, cell site outages due to stolen batteries, and poor management resulting in breaks in optical fibre. Lastly, there are natural disasters where outages result from heavy rainfalls, fibre is destroyed due to erosion, and cell sites experience downtime from flooding. These findings largely validate the assertions by the Ghana Commercial Bank Strategy and Research Department (2023); Jacobs (2022); Adel (2021); Bukhsh *et al.* (2020); Maseko (2019); and ENISA (European Union Agency for Network and Information Security, 2017).

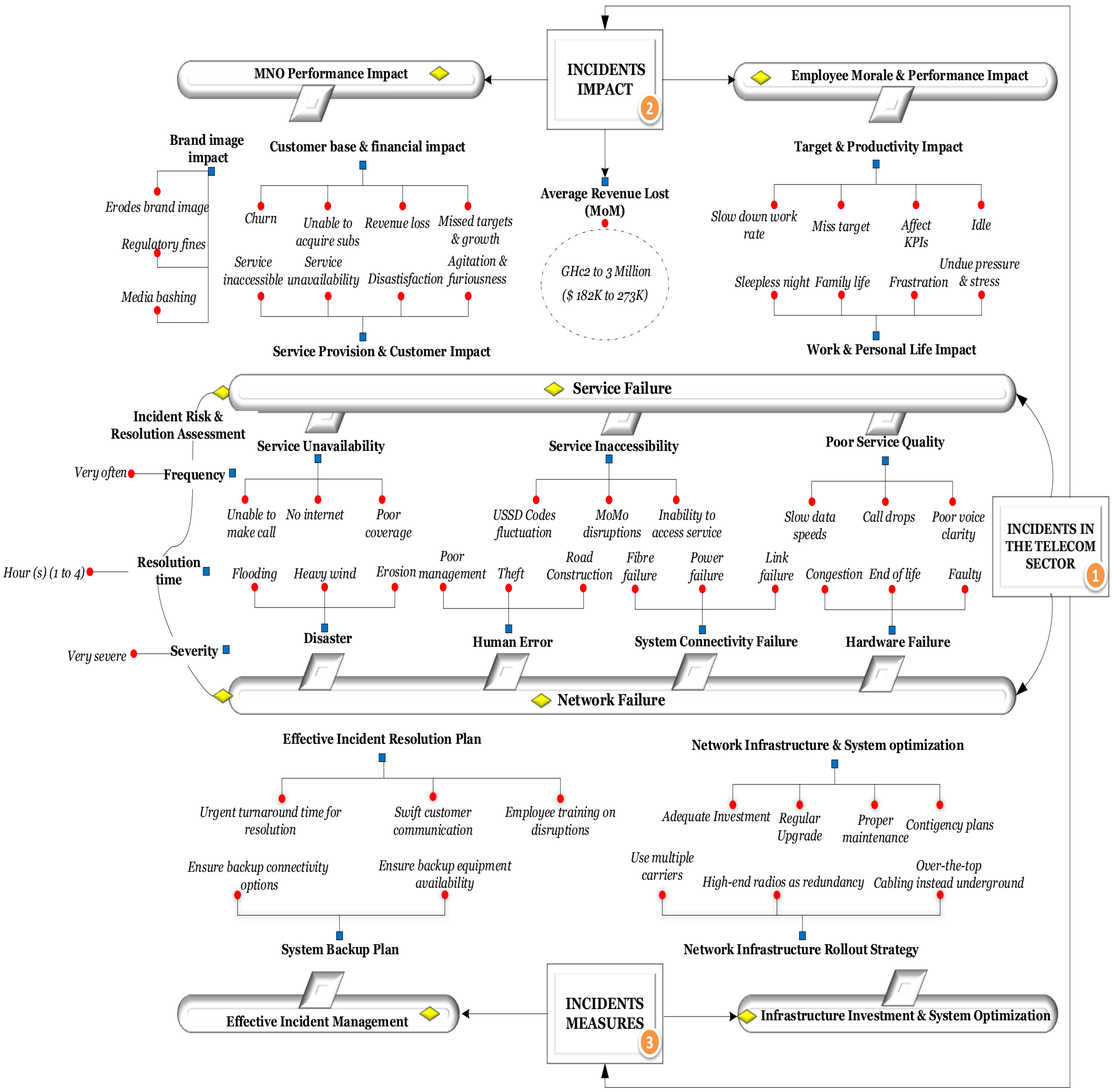

Figure 3: Telecommunications Sector Incidents Framework (Source: Researcher's own construct from the field data)

Service failure is a huge pain point for subscribers, as their entire lives are dependent on their telecommunication service availability. The incidents found in this category involve service unavailability where subscribers cannot make calls, there is no Internet, and network coverage is also poor, as asserted by Maya (2023); also, due to service inaccessibility, whereby USSD codes keep fluctuating, customers cannot use their mobile money wallets due to disruptions, and products and services cannot be accessed amidst the incidents. Finally, there is poor service quality, where subscribers experience slow data speeds, call drops, and poor voice clarity. These findings constitute a breach of quality of service (QoS) (NCA, 2023).

Figure 3 in relation to the incidents further indicates that the impact of these incidents is very severe, their frequency of occurrence is also very high, and it takes, on average, one to four

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hours for the incidents to be resolved for service restoration. These findings are a very important addition to the literature, as none has been found and validated scientifically.

Furthermore, in answering question two of the study — How do the incidents affect performance? — as shown in Figure 3, the study reveals that incidents in the telecommunications sector negatively impact employee and MNO performance. Employees become demoralized due to a lack of work-life balance, sleepless nights, frustrations, and undue pressure, which also affect productivity levels, hindering their ability to achieve performance targets. These findings validate assertions by Tams *et al.* (2022) and Asentria (2020). In relation to the MNO, the incidents impact their customer base and financials as subscribers begin to churn out and they are unable to acquire new subscribers, resulting in a huge revenue loss and affecting their growth, as observed by EY (2023). Also, MNOs' inability to provide service and satisfy customers amidst the incidents results in customer dissatisfaction as customers become agitated and furious. Lastly, MNOs' image is eroded due to public outcry, which to a large extent attracts regulator sanctions, validating assertions by NCA (2023) and Maseko (2019).

Finally, in answering question three — Approximately how much revenue is potentially lost due to the occurrence of these incidents? — the findings, as presented in Figure 3, revealed that the incidents result in an average revenue loss of GH₵ 2 to 3 million ($182K to $273K) per month. These findings are a very significant contribution to the literature owing to their sensitivity and confidentiality constraints.

Conclusion and Recommendation

The study adopted a multiple case-study approach to investigate incidents and their impacts on revenue in the telecommunications sector using data from mobile network operators (MNOs) in Ghana. Subsequent to the findings, as summarised in Figure 3, the study suggests measures to minimise incidents and impacts on MNOs' performance, including investing in network infrastructure, adopting a different rollout strategy, maintaining system optimization, having a contingency plan, well-trained employees, swift communication with customers, and urgent turnaround times for resolution.

In conclusion, the impact of these incidents is very severe, both on employees and operators' performance; their frequency of occurrence is also very high, and their restoration time is too long. This is a crucial issue that cannot be ignored; therefore, through the "*Telecommunication Sector Incidents Framework*", mobile network operators (MNOs) around the world could get a better understanding of the incidents in order to keep their occurrences to a manageable level, create an exceptional customer experience by reducing churn, and increase revenues.

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This study fills a gap in the literature on incidents and their revenue impacts in the telecommunications sector, providing a benchmark for future research in various countries. Nevertheless, this study focuses solely on mobile network operators' perspectives on the incidents within the context of the telecommunications industry in Ghana. Therefore, future studies can explore incidents from subscribers' points of view and how they affect their livelihood and business fortunes. Also, a study can quantitatively validate this proposed framework.

Acknowledgement

Special appreciation goes to the network, IT, and system engineers, as well as the commercial staff in the Ghanaian telecom industry, for taking the time to attend the long interviews in spite of their busy schedules. This study could not have come to fruition without their willingness to participate.

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Appendix 1: Incident posts on Facebook

Table A1. Incidents reported by Vodafone

Incidents' communication to customers	Date & Time	Areas Affected	Source
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Amasaman, Nsawam, Kotoku, Pobiman, Medie, Adieso, and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Sunday, September 24, 2023 at 3:45 pm	Some locations	https://web.facebook.com/vodafoneghana/posts/pfbid0zveo72z3z2M4n1x79f6BytrssukG8n9TvFjAzT4AuUpxcmBmCC6gczEiLNaDU4Bsl?__tn__=%2CO*F
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Winneba and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Wednes-day, September 13, 2023 at 7:40 am	A specific location	https://web.facebook.com/vodafoneghana/posts/pfbid02Lp28uQjtVrBzd1RaNHWugcbbMcHQb5JvbZ9rXNYgb8d5xjGAfXu5asVHpa9J7hXyl?__tn__=%2CO*F
Dear Customer, we sincerely apologise for the intermittent network challenges you may be experiencing using our mobile voice services at the moment. Our network engineers are on site working to resolve the as quickly as possible. Thank you.	Wednes-day, September 13, 2023 at 7:28 am	Nation-wide	https://web.facebook.com/vodafoneghana/posts/pfbid02WUpBc7JbgA6wQZ8rj43siNDdyp1GUN4ruxY7kVrFZCnKCh4d6vCwncgx8KifrQfhl?__tn__=%2CO*F
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Damanko, Kpandae,Bimbila, Bicheritanga, Kpassa, Wulensi, Tatale, Yendi and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Saturday, September 9, 2023 at 12:01 pm	Some locations	https://web.facebook.com/vodafoneghana/posts/pfbid019YHkAwcxtDQNPuhL8Du8YkAEJDgL3H7kEoS8JjQ4yj92AwVJzoyVfPjwN8dyuELl?__tn__=%2CO*F
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Sham, Ateiku, Gbedema and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Tuesday, August 15, 2023 at 10:34 am	Some locations	https://web.facebook.com/vodafoneghana/posts/pfbid0T95PyoJaBNwn8rKeje2rvZzaNWos5EVf1Snx2ZWV2Rd9EQ94TsRqXWpEnKAyyKi4l?__tn__=%2CO*F
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Gbawe, Manso Adubia, Barekese, New Adubiase, Apemenim,Takoradi Harbour, Patriensa, Kpembe, and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Friday, August 11, 2023 at 1:37 pm	Some locations	https://web.facebook.com/vodafoneghana/posts/pfbid0u2w8JtRF7fTr4nZ7iQinMS6wHpoLtSBiLN8CdyiEM6jWYoyC86nHwX7GhgHiucmcl?__tn__=%2CO*F
Dear Customer, we are currently experiencing challenges with our Mobile and Fixed services within Dominase, Tishigu, New Adubiase, Klagon,Larabanga,Kasoa,Gbewa,Oyibi, and its environs. Our engineers are on site working to resolve the challenges and restore services as soon as possible. We sincerely apologise for any inconvenience caused.	Sunday, August 6, 2023 at 6:06 pm	Some locations	https://web.facebook.com/vodafoneghana/posts/pfbid02hXmXHZqtH2oMjsSW47KBxRcRsFFw8RGnAvUtjhoESvq22Ee3Hc1eSRdKXEVwizvGl?__tn__=%2CO*F

Table A2: Incidents reported by MTN and AirtelTigo

Incidents' communication to customers	Date & Time	Areas Affected	Source

Y'ello Valued Customer, We apologize for the intermittent challenges you are experiencing in accessing MoMo services. This is because of a technical challenge. Our engineers are working to resolve the issue. We'll update you when the issue is resolved We sincerely apologise for any inconvenience caused.	Friday, September 29, 2023 at 11:48 am	Nationwide	https://web.facebook.com/MTNGhana/posts/pfbid02GyTAVK9bqa258wrR6QqVCacWiYUfwFWp58YHSLvhEh3b4mf6wePfhNkjuHMnGKeBl?__tn__=%2CO*F
Y'ello Valued Customer, we apologize for the intermittent challenges a cross-section of customers are experiencing in accessing data, voice, and MoMo services. This is as a result of a technical challenge. Our engineers are working to resolve the issue. We will keep customers updated when the issues is resolved.	Tuesday, September 26, 2023 at 2:26 pm	Nationwide	https://web.facebook.com/MTNGhana/posts/pfbid0h6S9giCjgYkTkce6K1uG3yJrqKkmYTb7LmY21nFKJAef6jcZXNsxzc1AfEjoCmQFl?__tn__=%2CO*F
Dear Valued Customer, we apologize for the intermittent challenges a cross-section of customers are experiencing in accessing data services. This is as a result of a technical challenge. Our engineers are working to resolve the issue. We will keep customers updated when the issues is resolved. We deeply apologise for the inconvenience caused.	Friday, September 22, 2023 at 7: 47 pm	Nationwide	https://web.facebook.com/MTNGhana/posts/pfbid0310evadk9JJNpBLW9U79WGSijNFG1ukSRQTV1JaRsF648KgiM62rHWPsJpMKmYBCNl?__tn__=%2CO*F
Y'ello Valued Customer, We wish to apologise to customers across the country for the intermittent challenges being experienced with mobile and broadband data services. We sincerely apologise for any inconvenience caused.	Thursday, August 17, 2023 at 11: 30 am	Nationwide	https://web.facebook.com/MTNGhana/posts/pfbid0Vcacj3aqQzYk26T72ZTi2eQJ2Fs2cCcDwkgjKD6RM3VbQvNzibH4pjDoSMM1UVj2l?__tn__=%2CO*F
We sincerely apologise for the challenges with our short codes and mobile app. Our engineers are working to resolve it as soon as possible.	Sunday, September 24, 2023 at 3:45 pm	Some locations	https://web.facebook.com/theatghana/posts/pfbid02K9UpFC7XBEGCakUUqzQxGHDCxvydQ5DhyFHiuE5jLvCqCuoYRwyj3pgAwWDbHpN4l?__tn__=%2CO*F
We sincerely apologise for the challenges with our ATMoney services. Our team is working to resolve this as soon as possible. Thank you.	Thursday, August 17, 2023 at 12:29pm	Nationwide	https://web.facebook.com/theatghana/posts/pfbid02BbDkV813U3pLXnanCgmX3G8Q3NEJe3e7bYhukYWuHnV7tRXADS5mbRWPnVyvyMoEl?__tn__=%2CO*F
Kindly be informed that we're experiencing service disruptions. Our team is working to restore the service as soon as possible. Thank you.	Friday, August 4, 2023 at 9:15am	Nationwide	https://web.facebook.com/theatghana/posts/pfbid0U76w6i3MnqsUbeeSo82jeLnzBioJZC3jx4xgGw2B5xVpMv9JLE9PWYcB5egFPiSUl?__tn__=%2CO*F
Dear Customer, We are currently experiencing slow internet service. Our engineers are working diligently to resolve the problem as soon as possible. Thank you for your patience.	Thursday, August 1, 2023 at 10:00am	Nationwide	https://web.facebook.com/theatghana/posts/pfbid02knp86ZVGUxNWMZE5KsF8hHoyTr7L6f4Chp9mjZWPgsU8Z87Riv7YQM4hCLuBwtRdl?__tn__=%2CO*F

Appendix 2: The Incidents in the Telecommunications Sector

RESEARCH QUESTION 1: What are the incidents in the Telecommunication Sector?

Participants Assigned Codes																			Sub-Codes	Categories	Themes	Aggregated Themes
A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	c5	c6	Total				
				*				*						*			*	4	*Faulty hardware*	Hardware Failure	Network Failure	Incidents in the Telecom Sector
*				*							*							3	*Hardware failure*			
						*								*				2	*End of life systems*			
		*		*			*				*		*	*			*	7	*Cell Sites (2G,3G, LTE) outages*			
								*									*	2	*Cell site congestion*			
*	*	*		*				*						*			*	7	*Power failure*	Systems Connectivity Failure		
	*							*			*			*			*	5	*Microwave link failure*			
													*	*			*	3	*Fibre failure*			
					*													1	*Wi-Fi disconnections*			
														*				1	*Loss of connectivity to OSS*			
	*			*									*					3	*Fibre cuts by road construction*	Human Errors		
														*				1	*Cell site outage due to stolen batter-ies*			
	*																	1	*Breaks in optical fibre*			
									*									1	*Outages due to heavy wind & rain falls*	Disaster		
									*									1	*Fibre destruction due to erosion*			
									*									1	*Cell sites downtimes by flooding*			
			*							*								2	*Unable to make calls*	Service Unavailability	Service Failure	
											*							1	*Inability to browse internet*			
					*													1	*No internet availability*			
						*							*					2	*Poor coverage*			
																*		1	*Network reception in emergencies*			
												*						1	*Inability to access shortcodes*	Service Inaccessibility		
															*			1	*USSD codes fluctuation*			
							*											1	*Mobile money disruptions*			
		*				*				*		*				*		5	*Unstable data connectivity*	Poor Service Quality		
						*	*								*			3	*Slow data speeds*			
		*	*															2	*Call drops*			
						*							*					2	*Poor voice clarity*			
				*					*									2	*Less severe*	Severity	Incident Risk Assessment	Incident risk and resolution assessment
*	*					*	*				*	*	*		*		*	9	*Severe*			
		*	*		*			*		*				*		*		7	*Very severe*			
*			*		*		*					*				*	*	7	*Often*	Frequency		
	*			*		*		*	*	*				*				7	*Sometimes*			
		*									*		*		*			4	*Always*			
									*									1	*Minute(s) (10 to 50)*	Resolution Time	Incident Resolution Assessment	
	*	*	*	*		*	*	*		*	*	*	*	*	*			13	*Hour(s) (1 to 4)*			
*					*											*	*	4	*Day(s) (1 to 5 days)*			

Appendix 3: The incidents' impact on MNO performance

RESEARCH QUESTION 2: How do the incidents affect performance?

Participants Assigned Codes																			Sub-Codes	Categories	Themes	Aggregated Themes
A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	c5	c6	Total				
														*				1	*Employees have sleepless night*	Employee Personal Life Impact	Employee Morale Impact	Incidents Impact Employees' Performance
																	*	1	*Affect employees family life*			
								*		*	*							3	*Employee become frustrated*	Employee Work Balance Impact		
								*		*			*	*			*	5	*Employees become pressured & stressed*			
*					*			*		*		*			*	*		7	*Affect KPI achievement*	Employee Target achievement impact	Employee Performance Impact	
		*																1	*Miss targets*			
						*												1	*Delay in performance reporting*			
*	*		*	*			*		*					*	*			8	*Slow down work rate*	Employee Productivity impact		
										*	*							2	*Employee become idle*			
						*						*						2	*Customer churn*	Customer Base Impact	MNO Performance Impact	Incidents Impact MNO's Performance
			*				*					*						3	*Difficult to acquire subscriber*			
*		*	*			*						*	*			*		7	*loss of revenue*	Financial Impact		
							*											1	*Impact new sales revenue*			
										*		*		*		*		4	*Affect company growth*	Targets Achievement Impact		
							*					*						2	*Impact company's monthly target*			
		*												*		*		3	*Unrealised company's target*			
					*						*		*					3	*Impact company performance reporting*	Performance Visibility Impact		
				*							*							2	*impact decision making process*			
	*																	1	*Service unavailability*	Service Provision Impact		
	*																	1	*Service inaccessibility*			
*																		1	*customers become agitated and furious*	Customer Satisfaction Impact	MNO image Impact	
	*					*			*						*	*		5	*Customer dissatisfaction*			
	*							*									*	3	*Regulatory sanctions (fines)*	Brand Image Impact		
						*												1	*Media bashing*			
									*	*							*	3	*Erode brand image*			
																*		1	*Communication challenges*			

Appendix 4: The revenue loss and measures to minimise incidents' occurrence

RESEARCH QUESTION 3: Approximately how much revenue is potentially lost due to the occurrence of these incidents?

Participants Assigned Codes																			Sub-Codes	Categories	Themes	Aggregated Themes
A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4	c5	c6	Total				
	*		*	*	*	*		*	*		*	*		*		*	*	12	*Unable to disclose*	Hesitation & lack of information	Revenue Lost	The amount of revenue lost due to the incidents' occurrence
			*									*						2	*It depends on the degree of occurrence*			
		*																1	*Average GHc 100K loss of revenue daily*	Loss of revenue disclosure		
*													*		*			3	*An average of GHc2 to 3 million, Month-on-Month (MoM)*			
							*			*								2	*Approximately, GHc1 to 2 million, Month-on-Month (MoM)*			
	*																	1	*Adequate infrastructure investment*	Network infrastructure investment	Network Infrastructure Investment & System Optimization	Measures to minimise incidents' occurrence and impact on performance
								*	*									2	*Investment for system upgrade and maintenance*			
				*														1	*Leveraging over-the top cabling instead of underground*	Network infrastructure rollout strategy		
				*														1	*High-end radios as redundancy*			
														*				1	*Utilize multiple carriers*			
																*		1	*Well-maintained network infrastructure*	System Optimization strategy		
																	*	1	*Regular hardware system upgrades*			
						*	*					*						3	*Contingency plans & Stable platforms*			
*																		1	*Urgent turnaround time for resolution*	Effective incident resolution plan	Effective Incident Management	
*											*				*			3	*Swift customer communication*			
										*								1	*Employee training on disruptions*			
			*															1	*Ensure backup equipment availability*	System backup plan		
													*	*				2	*Ensure backup connectivity options*			

Charles Todd and the Overland Telegraph Line

A Book Review of "Mr Todd's Marvel"

Jim Holmes
President, TelSoc and Director, Incyte Consulting

Abstract: Adam Courtenay, an Australian author and journalist completed *Mr Todd's Marvel: How one man telegraphed Australia to the modern world*, a recent book on Charles Todd and the Overland Telegraph Line (OTL), in time for it to be published around the 150th anniversary of the completion of the historic project. Although the book concentrates on the immense task and challenges of building the OTL from Port Augusta to Palmerston (now called Darwin), it does provide a focus on the people that participated and, especially, on the special role of Charles Todd. This book review concludes that the book is a useful introduction to the subject, with occasional inclusions of information that might not be well known, and permits the reader easy access to the subject through its narrative style and generous spread of illustrations.

However, the book does have limitations. It lacks an index and citations detailed enough to be followed up. For the reader who might wish to pursue particular issues or events, these limitations are frustrating indeed. Overall, it is for the general reader, rather than for those seeking to gain an even deeper understanding of the times, the project, and the major participants and their motivations.

Keywords: Charles Todd, Overland Telegraph Line, Australian telecommunications

Introduction

Mr Todd's Marvel (Courtenay, 2023) is the latest book on the substantial Victorian-era infrastructure achievement, the building of the Overland Telegraph Line (OTL) that connected Port Augusta (and Adelaide) to Palmerston, as Darwin was then known, and so connected Australia to the cable systems that were being deployed in the British Empire, Europe and America. The book is written in a readable style by Adam Courtenay, a Sydney-based author and journalist.

Unlike some other recent books on Todd, such as *Beyond the Legend: The Many Worlds of Charles Todd* by Denis Cryle (Cryle, 2017), which was reviewed in the *Journal* (Holmes, 2018), this book is not a biography as such, but focusses very much on the OTL. It was timed by the author to coincide with the 150th anniversary of the completion of the OTL in August 2022, although it was published in 2023.

My interest is what the book says that is new and worthwhile about Todd and his achievement that has not been said or covered already.

Structure

The book is fairly short at 197 pages, including a foreword by a descendant of Charles Todd and a useful bibliography. It includes a lot of illustrations. Regrettably there are no detailed citations. The book is set out chronologically in 12 chapters plus an epilogue, in which Courtenay provides an overall assessment of Todd and the OTL and its significance for Australia's development. But we know from the outset, by the title and the subtitle ("How one man telegraphed Australia to the modern world"), something about that conclusion and the importance attributed to Todd himself.

Chapter 1: Not so Great Connections

Courtney describes the celebrations in New York following the completion of a telegraphic cable across the Atlantic, and the receipt of the first transatlantic message from Queen Victoria to President James Buchanan. He relates the well-known story of how the cable failed some few weeks later (Courtenay, 2023, p. 15): hence the chapter title.

At the same time, in Australia, John McDouall Stuart was exploring the northern and western regions seeking evidence of an inland sea in areas that had not been visited by Europeans. Stuart's explorations and maps subsequently became critical inputs for planning and building the OTL on a sustainable route.

Todd is introduced at the end of the chapter. He is credited with "understanding better than most" that "Stuart was paving the way for a great telegraph line that would connect Australia to the world"(Courtenay, 2023, p. 21). This may well be the case, but Courtenay offers no citations to support his conclusion about Todd at this point. There are no footnotes or endnotes in the book at all, suggesting to this reviewer that it was intended only for the general reader.

Chapter 2: The Road to Adelaide

In this chapter, Courtenay describes Todd's background and his career in England where, by 1855, he was a 'supernumerary computer' working at the Royal Observatory at Greenwich (Courtenay, 2023, p. 23). Todd's talents as a gifted mathematician and as a capable astronomer are mentioned, as well as his association with telegraph systems used to

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coordinate and set timing for railway, navigation, and other applications. Courtenay does not dwell on this part of Todd's life, because, as mentioned already, this is not a biography of Todd.

Courtenay describes how the career opportunity in the colony of South Australia arose and how Todd came to be considered for it. The position was described as 'an observer' who was "qualified to make astronomical and meteorological observations, having some knowledge of the working of an electric telegraph, and competent to act as the head of a Department" (Courtenay, 2023, p. 23). Todd was not the first choice for the job. At the time he set sail for South Australia, in July 1855, neither Burke and Wills, nor Stuart, had commenced their explorations of the Australian outback, and long-distance telecommunications connecting the colonies to the world were well into the future.

Courtenay attributes to Todd a very early vision at this time to see a "telegraph string round the world", based on a speech said to have been made at his wedding (Courtenay, 2023, p. 33). Courtenay may well be right, but, unfortunately, he has provided no further evidence or citations on this point. What exactly drove Todd, and excited his curiosity and ambition, is important to understanding later events and his eventual success.

Chapter 3: The Hub of the South

Courtenay describes in this chapter the colony in Adelaide when Todd arrived, only 19 years after its foundation. He offers some interesting insights into the nature of the colony and how it differed from others in Australia. In less than 20 years the population had grown to 155,000 and it attracted "artisans and professionals who lacked opportunity in the mother country" (Courtenay, 2023, p. 35).

In 1855, Todd was both the Superintendent of Telegraphs and the colony's Astronomical Observer (Courtenay, 2023, p. 38). One of his first projects was to establishment a government telegraph line from Adelaide to Port Adelaide and to buy out a private competitor (Courtenay, 2023, p. 39). The ACCC clearly did not exist then! The South Australian colonial network was then extended from Adelaide to other towns. In 1856, Todd agreed with his Victorian counterpart to jointly erect a telegraph line to Melbourne. This was completed in July 1858 (Courtenay, 2023, p. 42) and Adelaide could also connect via that link to Sydney.

Courtenay well describes the competition that was emerging in the plans for overseas connection. The main competition was from Queensland, which proposed to connect via Darwin to Batavia (Jakarta) and beyond. This started in 1858 and continued for the next 15 years, on and off. The failure of the transatlantic cable in 1858 led to a pause, as did the United States civil war.

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Chapter 4: The Gaps begin to Close

Courtenay describes the advances in cable design and manufacture that occurred after the 1858 transatlantic failure. The section on how Todd managed to win the British Australia Telegraph Company (BAT) contract to build a telegraph line to connect with BAT's cable once landed in Darwin is particularly interesting, although there appears to be no new information or insights.

Chapters 5 to 11

These chapters make up the bulk of the book and are concerned with the monumental planning, logistics and construction tasks that Todd had to address in delivering the OTL in incredibly challenging circumstances. The challenges were not all from operating in barely explored and unexplored country far from white settlement. The poor management of the operation in the northern section is well described and the mutiny of the workers at critical times is mentioned. In addition, time was of the essence, because of the substantial penalties for exceeding deadlines in the BAT contract.

These chapters are well written and well supported with illustrations and appropriately detailed maps of the Southern, Northern and Central Sections into which Todd divided the project. Work proceeded more or less simultaneously on all three Sections to meet the contract timetable. In the event, the overall deadline was not met, and the overrun was around 6 months. Todd and South Australia were saved from substantial contractual penalties by the good fortune that BAT had failed to land a working cable on time in Port Darwin. Even so, the OTL budget was seriously exceeded. The actual expenditure was around £480,000 [about £21.0M or AUD 40.5M in 2024], four times Todd's original estimate (Courtenay, 2023, p. 164). Courtenay notes that "few complained" about this overrun, but provides no supporting evidence. He does, however, record that "within a year, South Australia had received £3,600 from local traffic charges and more than £12,000 from overseas cables" (Courtenay, 2023, p. 167). After operating costs, these revenues would seem to pale against the overrun. There were major economic benefits from the OTL and cable connectivity to overseas export markets, however, to which Courtenay refers (Courtenay, 2023, pp. 167 and 169).

The OTL Sections were finally connected up on 22 August 1872 at Frew Ponds Repeater Station between Daly Waters and Tennant Creek in the Northern Section. The line had to be cut and rejoined for the ceremony. Re-enactments for media coverage are clearly not 20th or 21st century inventions. I will not spoil by retelling Courtenay's wonderful and humorous description of the embarrassment that resulted when it was found that too much of the line had been cut and could not be readily rejoined (Courtenay, 2023, pp. 159–160).

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At the end of Chapter 11, Courtenay offers a very useful but highly summarised account of what happened to Todd and what happened to the OTL after 1872. The OTL was duplicated in 1898 by a copper wire system and used for voice as well as telegraph services from 1925. The line was becoming increasingly redundant as the 20th century wore on (Courtenay, 2023, pp. 169 and 171).

Chapter 12: The Great Incursion

The impact of the OTL and white settlements around the repeater stations on indigenous peoples is discussed in some detail in the last chapter. At first this looks like an afterthought, and it may have been that. However, it does deserve a separate chapter, because the timescales of European and indigenous interaction along the length of the OTL is different from the sequential approach of the preceding chapters, with their focus on the period from 1870 to 1872.

The most violent events at Barrow Creek in February 1874 are covered, including the further violence that followed and the punitive expedition which followed, resulting in atrocities against the Kaititja people (Courtenay, 2023, pp. 183–184; see also Jones, 2023).

What We Learn of Todd

As already mentioned, Courtenay does not intend this book to be a biography of Todd, and refers to Denis Cryle as Todd's biographer (Cryle, 2017). Nevertheless, it is impossible for Courtenay not to convey something of Todd in the way Todd manages monumental tasks under very difficult circumstances. In the final section (not accorded chapter status) of the book, entitled 'Epilogue', Courtenay assesses Todd the man. He refers to Todd's wide range of abilities and interests from telegraphy to meteorology, astronomy, scientific endeavour generally, electricity and power generation, and other important issues of the day. He refers to Todd as selfless and self-deprecating, and not the least self-congratulatory (Courtenay, 2023, p. 190). Courtenay considers that Todd was great also because "he had the common touch" and could get the best out of situations by "his ability to gently influence others for the greater good" (Courtenay, 2023, p. 194).

Courtenay concludes: "Todd was a great leader capable of moving men and material across a continent. And that's the thing about great leaders — they never boast" (Courtenay, 2023, p. 194).

What We Learn of the Overland Telegraph Line

I do not think that we learn anything new about the OTL from this book. It is a derivative work relying on much that has already been published, rather than a work describing new research into new sources. It is still a good read and a tale well told for all that, and I believe that was the intention of the author.

Conclusion

I recommend this book as a sound retelling of the story of the OTL, including how it came to be a project of the Colonial Government of South Australia, the context in which it was conceived and won, and the challenges of its planning, delivery and operation. It is intended for the general reader rather than for the researcher or those with specialised interests associated with aspects of the topic. That probably explains the unfortunate lack of detailed citations. However, it does not explain the lack of an index.

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The Australian East-West Radio Relay System Revisited

Simon Moorhead
Telecommunications Manager

Abstract: The *Journal* revisits an historic paper from 1971 by R. W. Richards and J. Donovan of GEC-AEI Telecommunications on the prime contractor's role in the delivery of the Australian East-West radio relay system from Northam in Western Australia to Port Pirie in South Australia.

Keywords: History of Australian Telecommunications, East-West Radio Relay System, GEC Australia, GEC-AEI Telecommunications, John A. Lush

Introduction:

Today Australians are largely immune to the challenges that "the tyranny of distance" presented to their forebears only a generation ago. The inability to access telecommunications services due to terrestrial isolation has largely been overcome with technological advances. Now there is an insatiable appetite for bandwidth everywhere in Australia and the optical fibre systems installed between Perth and Adelaide are capable of supporting millions of equivalent voice circuits.

Until the late 1960s, the East-West link between Adelaide and Perth used voice frequency telegraphy and HF transceivers to provide a limited number of voice circuits across the Nullarbor Plain. The Postmaster General's Department (now Telstra) called for world-wide tenders closing in January 1966 (Figure 1), for the supply and installation of a broadband communication system linking the broadband networks of Eastern and Western Australia ("Broadband Communications System", 1965).

The tender schedule specified a microwave radio system, but also set out the requirements for a co-axial cable system as an alternative. Furthermore, the tender invited other system solutions that the tenderer might consider suitable. The route distance was around 2,400 kilometres and most terrestrial sites would be off the mains power grid. Therefore, reliability

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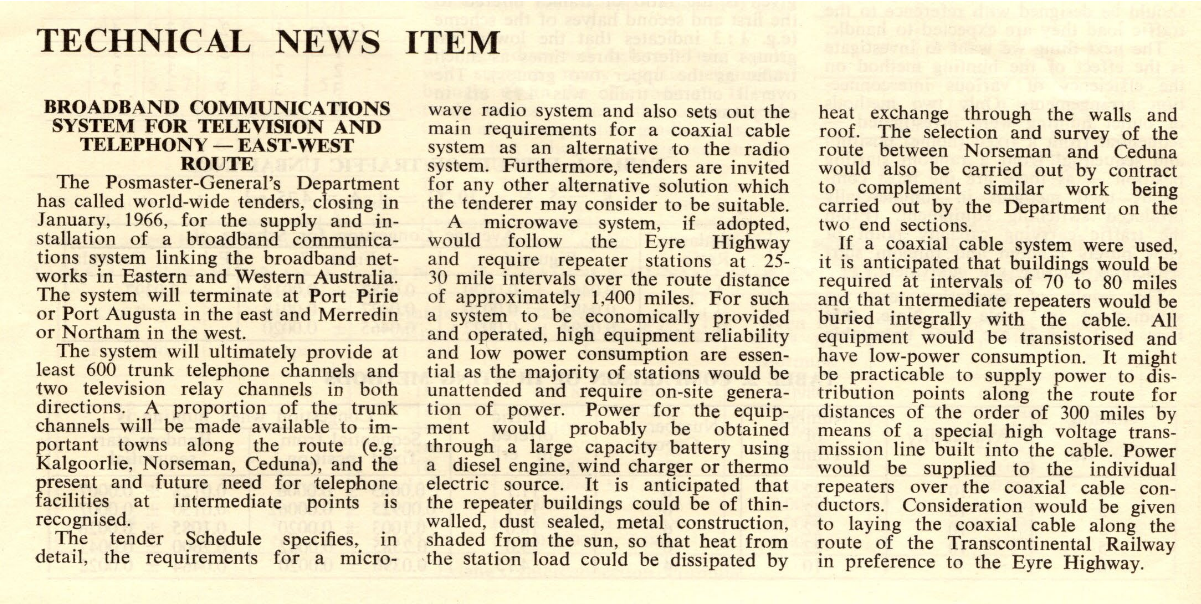
in passively cooled equipment shelters and low power consumption were prime considerations.

Twenty-eight companies were invited to tender for a 60-hop system from Northam in Western Australia to Port Pirie in South Australia. They were to provide 1+1 both-way, 600-circuit telephony bearers, capable of carrying television on the standby bearer on an occasional basis. The system had to cater for the possible expansion of up to six radio bearers in either direction, which influenced the design of tower, shelter and power requirements.



TECHNICAL NEWS ITEM

BROADBAND COMMUNICATIONS SYSTEM FOR TELEVISION AND TELEPHONY — EAST-WEST ROUTE

The Posmaster-General's Department has called world-wide tenders, closing in January, 1966, for the supply and installation of a broadband communications system linking the broadband networks in Eastern and Western Australia. The system will terminate at Port Pirie or Port Augusta in the east and Merredin or Northam in the west.

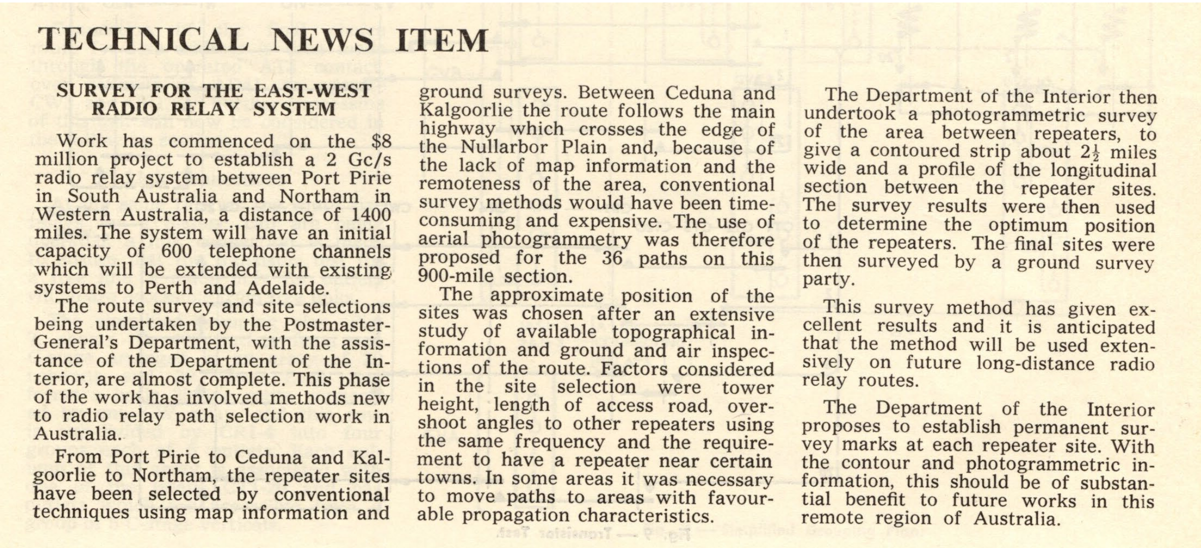
The system will ultimately provide at least 600 trunk telephone channels and two television relay channels in both directions. A proportion of the trunk channels will be made available to important towns along the route (e.g. Kalgoorlie, Norseman, Ceduna), and the present and future need for telephone facilities at intermediate points is recognised.

The tender Schedule specifies, in detail, the requirements for a microwave radio system and also sets out the main requirements for a coaxial cable system as an alternative to the radio system. Furthermore, tenders are invited for any other alternative solution which the tenderer may consider to be suitable.

A microwave system, if adopted, would follow the Eyre Highway and require repeater stations at 25-30 mile intervals over the route distance of approximately 1,400 miles. For such a system to be economically provided and operated, high equipment reliability and low power consumption are essential as the majority of stations would be unattended and require on-site generation of power. Power for the equipment would probably be obtained through a large capacity battery using a diesel engine, wind charger or thermo electric source. It is anticipated that the repeater buildings could be of thin-walled, dust sealed, metal construction, shaded from the sun, so that heat from the station load could be dissipated by heat exchange through the walls and roof. The selection and survey of the route between Norseman and Ceduna would also be carried out by contract to complement similar work being carried out by the Department on the two end sections.

If a coaxial cable system were used, it is anticipated that buildings would be required at intervals of 70 to 80 miles and that intermediate repeaters would be buried integrally with the cable. All equipment would be transistorised and have low-power consumption. It might be practicable to supply power to distribution points along the route for distances of the order of 300 miles by means of a special high voltage transmission line built into the cable. Power would be supplied to the individual repeaters over the coaxial cable conductors. Consideration would be given to laying the coaxial cable along the route of the Transcontinental Railway in preference to the Eyre Highway.

Figure 1. Notice of the call for tenders ("Broadband Communications System", 1965)



TECHNICAL NEWS ITEM

SURVEY FOR THE EAST-WEST RADIO RELAY SYSTEM

Work has commenced on the $8 million project to establish a 2 Gc/s radio relay system between Port Pirie in South Australia and Northam in Western Australia, a distance of 1400 miles. The system will have an initial capacity of 600 telephone channels which will be extended with existing systems to Perth and Adelaide.

The route survey and site selections being undertaken by the Postmaster-General's Department, with the assistance of the Department of the Interior, are almost complete. This phase of the work has involved methods new to radio relay path selection work in Australia.

From Port Pirie to Ceduna and Kalgoorlie to Northam, the repeater sites have been selected by conventional techniques using map information and ground surveys. Between Ceduna and Kalgoorlie the route follows the main highway which crosses the edge of the Nullarbor Plain and, because of the lack of map information and the remoteness of the area, conventional survey methods would have been time-consuming and expensive. The use of aerial photogrammetry was therefore proposed for the 36 paths on this 900-mile section.

The approximate position of the sites was chosen after an extensive study of available topographical information and ground and air inspections of the route. Factors considered in the site selection were tower height, length of access road, overshoot angles to other repeaters using the same frequency and the requirement to have a repeater near certain towns. In some areas it was necessary to move paths to areas with favourable propagation characteristics.

The Department of the Interior then undertook a photogrammetric survey of the area between repeaters, to give a contoured strip about 2½ miles wide and a profile of the longitudinal section between the repeater sites. The survey results were then used to determine the optimum position of the repeaters. The final sites were then surveyed by a ground survey party.

This survey method has given excellent results and it is anticipated that the method will be used extensively on future long-distance radio relay routes.

The Department of the Interior proposes to establish permanent survey marks at each repeater site. With the contour and photogrammetric information, this should be of substantial benefit to future works in this remote region of Australia.

Figure 2. Notice of commencement of work ("Survey", 1967)

Survey work on the route began in 1967 (Figure 2). The General Electric Co. of Australia Ltd (GEC Australia) (Figure 5) won the tender. The historic paper (Richards & Donovan, 1971) describes how GEC Australia enlisted the help of GEC-AEI Telecommunications Ltd to prepare the tender submission, manage the UK post-contract organisation, and to liaise with GEC Australia on the Australian post-contract organisation, delivery and commissioning.

At the time, it was the largest broadband microwave project ever undertaken by the Postmaster General's Department. The total cost of the system was around $11 million which is equivalent to $140 million today (March 2024).

The historic paper is unique in that it provides details on project management that would normally be kept confidential to the tenderer. Aspects such as pre-tender investigations, post-contract organisation, communications and training are discussed in depth. This is typical of times when technical achievements were shared amongst the industry and before competitive advantage closed the door to publication in journals such as this.

I would also like to draw the reader's attention to the other excellent technical papers on the East-West Radio Relay System which appeared in this Special Issue (Figure 3) of Volume 21, Number 1, 1971 of the *Telecommunication Journal of Australia*, as follows (Figure 4):

- A.P.O. Project Management – pp. 8–15
- Testing the Prototype Equipment – pp. 16–23
- The Design and Development of the Radio and Associated Equipment – pp. 24–52
- Installation and Commissioning Requirements – pp. 53–58
- Stressed Rock-Anchor Antenna-Support Towers – pp. 59–62
- Thermal Design of Naturally Cooled Repeater Shelters – pp. 63–64
- Environmentally Controlled Equipment Shelters – pp. 66–71
- Antennas and Feeders – pp. 72–79
- Power Plant – pp. 80–94
- Service Aspects of the Radio System – pp. 95–98
- Operations and Maintenance – pp. 99–100

Dedication

This historic paper reprint is dedicated to John A. Lush (18 February 1947 – 28 December 2023) who came to Australia in 1969 as part of the GEC East-West project team. John settled in Australia and went on to a distinguished career in telecommunications at Telecom Australia, Andrew Antennas and LSE Technology.

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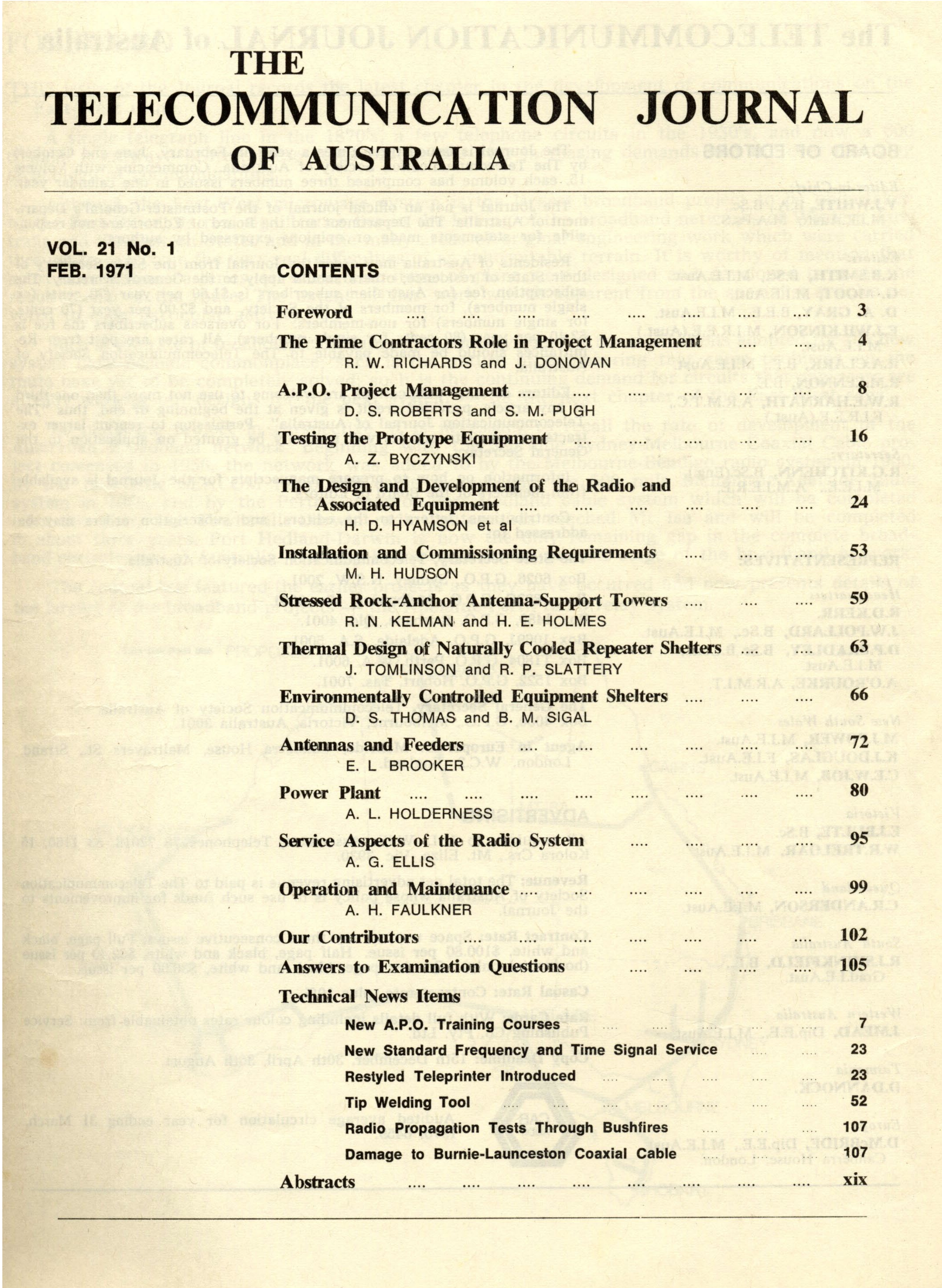
Figure 3. The cover of the TJA special issue on the East-West Microwave link, February 1971



THE TELECOMMUNICATION JOURNAL OF AUSTRALIA

VOL. 21 No. 1
FEB. 1971

CONTENTS

Figure 4. The Table of Contents of the TJA special issue on the East-West Microwave link, February 1971

The Historic Paper

THE PRIME CONTRACTOR'S ROLE IN PROJECT MANAGEMENT

*R. W. RICHARDS AND J. DONOVAN**

INTRODUCTION

In any large project there is much liaison and co-ordination effort required on equipment and services which are not normally part of a prime contractor's manufacturing capability, but nevertheless form part of his contractual responsibility. GEC-AEI Telecommunications Limited (the UK-based company responsible for the telecommunications activities of The General Electric Company Limited, of England) was well equipped to act as the essential keystone vital to the success of any large telecommunications project. The East-West system is a typical application of this expertise.

A UK-based project management team, unique to the project, was appointed as soon as the 'Invitation to Tender' was issued, and later supplemented by a Melbourne-based team to ensure maximum communication between customer and suppliers. This article presents the scope of the problem and illustrates the means subsequently used to co-ordinate all aspects of the Contract. Particular reference is made to one contractual responsibility; that of training A.P.O. engineers and technicians in the operation and maintenance of the advanced and sophisticated all-semi-conductored equipment supplied.

THE INVITATION TO TENDER

GEC (Australia) Pty Ltd was one of 28 companies invited to tender for the 2400 km (1500 mile) Northam to Port Pirie Microwave radio system for trunk-telephone and television transmission (Fig. 1). The 60-hop system was to provide 1 + 1 bothway 600-circuit telephony bearers between Northam and Port Pirie, capable of carrying television over the standby channel on an occasional basis. A unidirectional television channel was required between Northam and Kalgoorlie. In addition, 'wayside' telephone channels were to be provided for settlements along the Eyre Highway. The requirement for space diversity operation over particularly difficult sections of the route was known, although the details were finalized later. The invitation to tender also

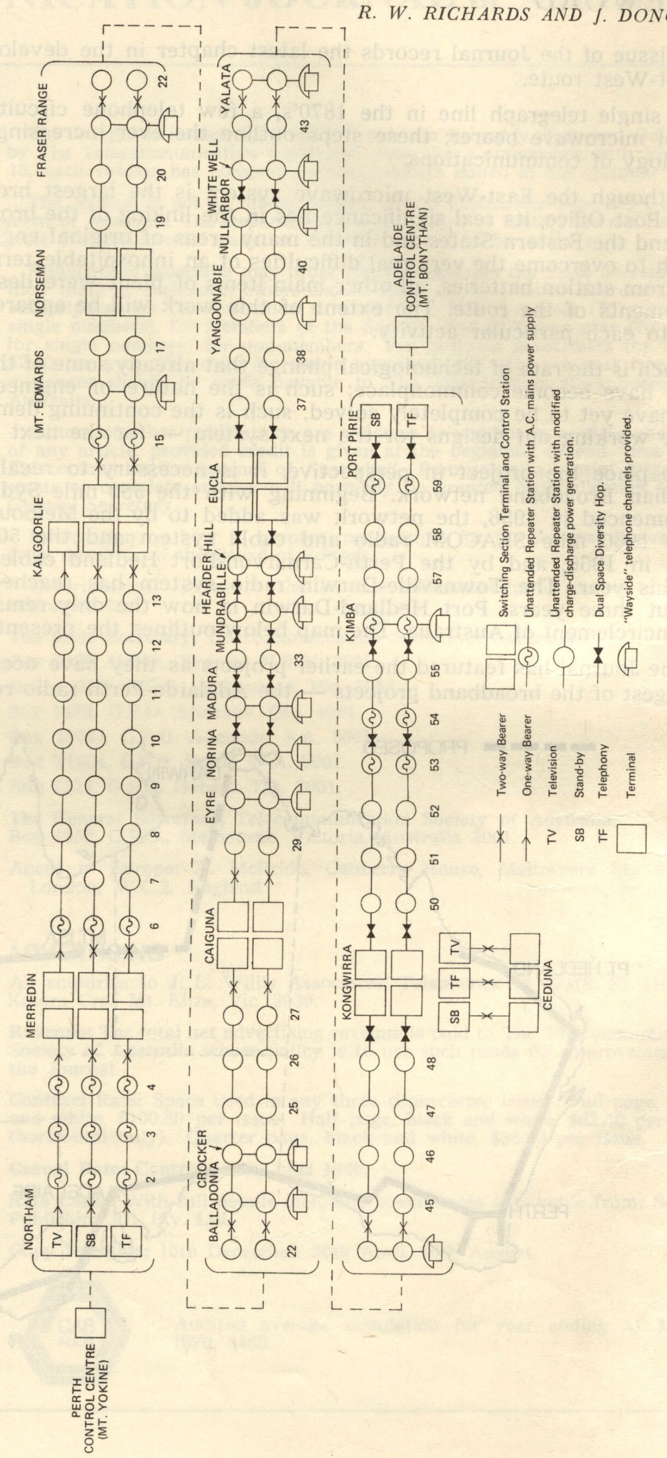


Fig. 1 — Simplified Route Plan

* Mr Richards is U.K. Project Manager and Mr Donovan is Australian Project Manager, East-West Project, for GEC-AEI Telecommunications Ltd, England

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specified the requirements for shelter and tower foundations, towers, equipment shelters for 51 unattended repeater stations, power-generation plant, antennae and feeders, and the supervisory and control scheme to be operated from control centres near Perth and Adelaide; intermediate control and switching stations were to be provided at Merredin, Kalgoorlie, Norseman, Caiguna, Eucla, and Kongwirra.

1 + 2 bothway telephony and television bearers between the satellite earth station at Ceduna and the adjacent intermediate control station at Kongwirra were added later.

The system had to take into account future expansion of the system up to a maximum of 6 radio bearers in each direction. For example, this influenced the shelter, tower and power generation considerations.

In addition to the technical requirements, the invitation to tender offered a wealth of information on the environment and discussed the problems with which a contractor was likely to be faced, and formed a sound foundation for the resulting tender.

PRE-TENDER INVESTIGATIONS

GEC (Australia) Pty Ltd enlisted the aid of GEC-AEI Telecommunications Ltd, who accepted responsibility for preparing a tender for submission to the A.P.O.

As soon as the invitation to tender was issued a project manager and a team of systems-planning, contract-engineering, and installation and commissioning experts, who were responsible for the complete preparation of the tender working in close co-operation with their colleagues in the Australian company, were appointed.

GEC experts visited Australia to make a comprehensive appraisal of potential subcontractors needed for the supply of ancillary equipment. Due account was taken of the local expertise that would be required, as well as transport considerations and freight economy, and it was decided that towers, shelters, and prime-power generation equipment should be manufactured in Australia. The team of experts also visited the repeater sites proposed by the A.P.O. to elaborate on the information provided in the invitation to tender, thus giving first-hand knowledge of site-access, environmental, and logistics problems.

Information obtained during the investigations, and from concurrent discussions with the A.P.O., was fed back to the U.K. for inclusion in the GEC proposals.

The project team was responsible for the collation of all incoming information and for the co-ordination of all the design and development activities. It was also responsible for co-ordination and liaison between all internal departments, subcontractors, the GEC teams in Australia, and the customer.

As an example of the co-ordination problem involved, it became obvious that all means possible would have to be used to reduce the overall prime power requirement, with minimum degradation of system performance. A.C. mains supply is not available at most of the unattended repeater stations, and these stations would normally be totally dependent on diesel generators. The route is effectively only accessible from the ends, therefore fuel transport costs are high. These factors led to the proposal of a low-power consumption version of the GEC 2 GHz radio system in which the total power consumption of a 1 + 1 bothway unattended repeater, with subtrafficband access, was reduced to about 500 W. This drastically altered the approach to shelter and power-generation design and gave rise to the shelter design that did not need powered equipment to control its environment and the modified charge-discharge system of power generation, the principles of which are described in individual articles.

Thus it will be appreciated that the early appointment of a centralized management team, can provide invaluable liaison and co-ordination between customer and suppliers.

Shortly before the tender was submitted by GEC (Australia) Pty Ltd, the project manager visited Melbourne to co-ordinate the activities of potential subcontractors and compile the comprehensive tender documents.

POST-CONTRACT ORGANIZATION

GEC retained two design consultants, Ove Arup and Partners for towers and foundations, and D. S. Thomas and Partners for the equipment shelters. The companies to whom GEC awarded the various subcontracts were Electric Power Transmission Pty Ltd for foundations and towers, Signal Industries Pty Ltd for equipment shelters, McColl Electric Works Pty Ltd for power equipment, and Andrews Antennas Pty Ltd for antennae and waveguide.

A team was set up in Australia, based in Melbourne, to prepare detailed information on such matters as station layout, site and foreground clearance. The role of the U.K. project management team changed from one of contract negotiation to one of co-ordination of design, manufacture, and supply. At this stage, the final format of the project management teams came into operation. A simplified liaison-path diagram of the Anglo-Australian partnership set up by the company is shown in Fig. 2.

The Project Manager in the U.K. had to ensure that each factory department, and U.K. supplier, received sufficient information on planning and progress associated with both U.K. and Australian phases of the project in order that all the committments could be met. He was also responsible for the commercial decisions necessary to maintain close control over the project. He was able to draw on the specialist expertise available at Coventry.

The GEC Project Manager at Melbourne, assisted by a project co-ordinator, was responsible for the co-ordination of all aspects of the project in Australia. Their team included a financial controller, specialist project engineers, field contract controller, sub-contractor's factory inspectors, and field surveillance engineers. The respective responsibilities are shown in Fig. 3.

COMMUNICATIONS

Telex and telephone communications were maintained between the UK-based GEC company, the Melbourne office, the field contract-control office (initially in Adelaide, later moved to Perth), and the field support centres at Ceduna and Northam (later moved to Norseman).

An appraisal of existing means of communication along the route indicated that the increased telephone activity would not overload the local public telephone network at the end sections, but that the public system would not cope on the centre section — the only communication with Eucla was a single-wire earth-return circuit which followed the original telegraph route of 1875.

These facilities were augmented by a temporary HF mobile radio network with base stations at the two field support centres and 21 mobile sets for the teams.

As each microwave radio-relay station became operational, additional communication was provided back to the terminal stations via the supervisory engineers' order wire circuit.

TRAINING

The contract included comprehensive instruction on all aspects of the system and its constituent equipments for the 45 A.P.O. maintenance technicians who were to be assigned to the route. A training establishment was set up at Whyalla (station 59) to

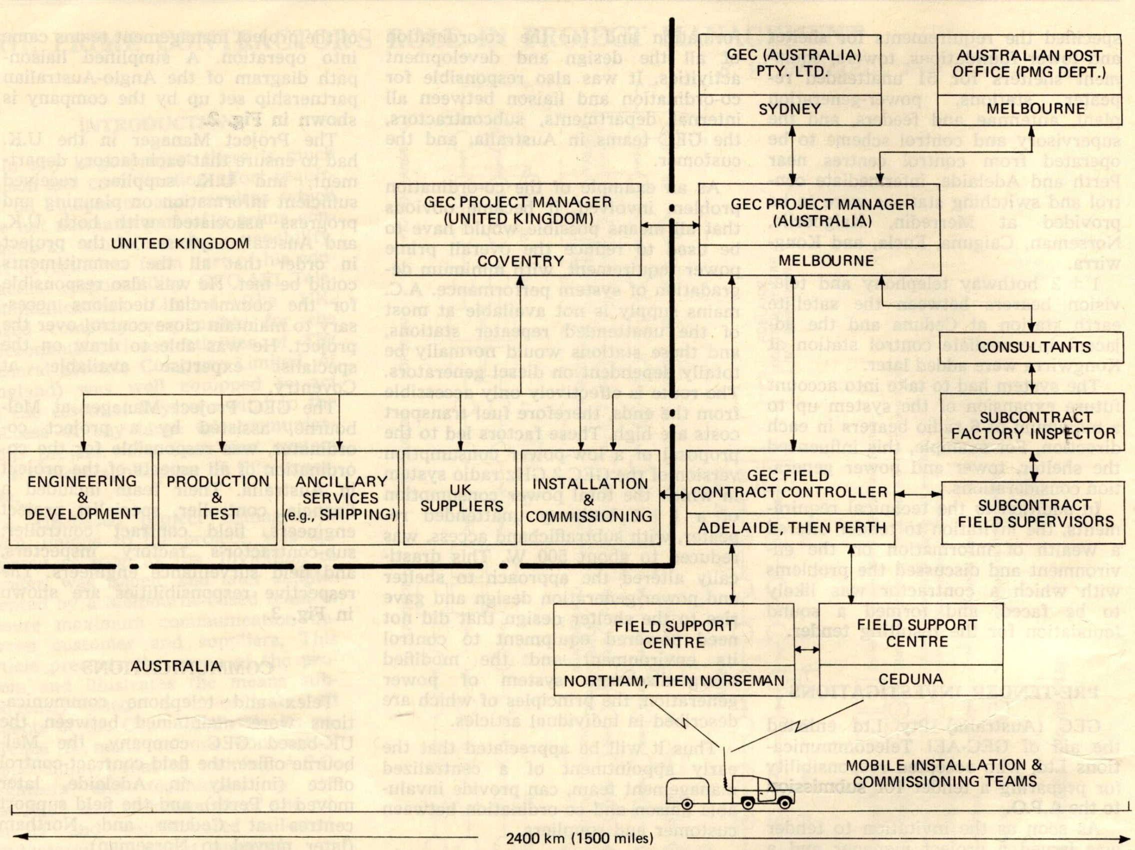

Fig. 2 — Simplified Liaison-Path Diagram of Project Organisation

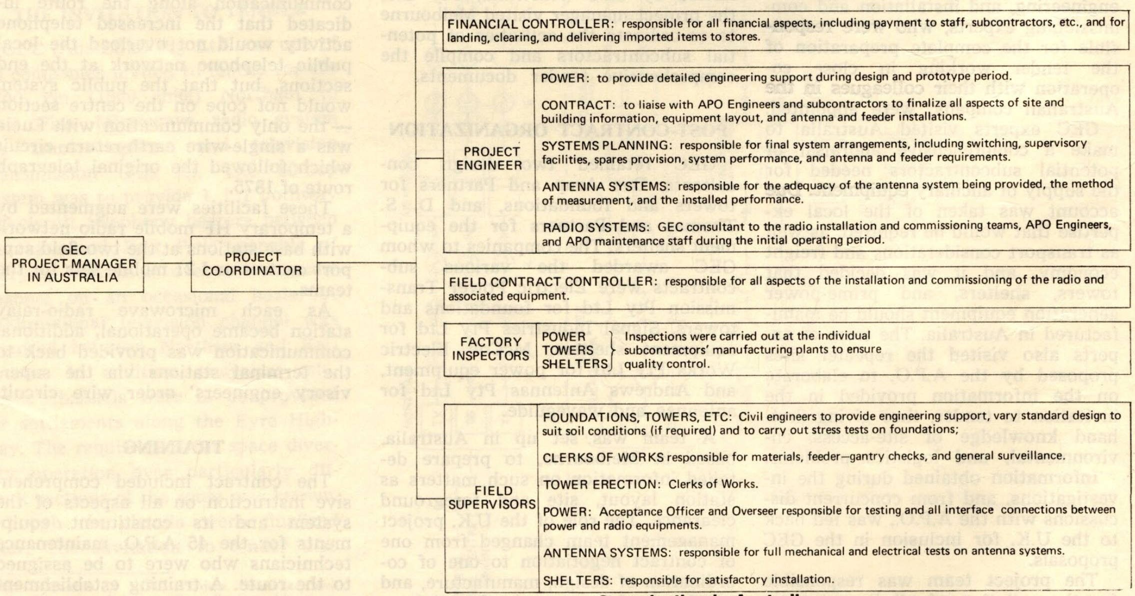

Fig. 3 — Project Management Organisation in Australia

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simulate a switching-section terminal, and provision was made to transmit to the next repeater along the route (Broadbents Hill) and back. GEC specialists, in co-operation with A.P.O. training officers, conducted two four-week courses in the theoretical and practical aspects of the system, its operation, and its maintenance. Instruction on the power equipment was given by McColl Electric engineers.

CONCLUSION

The article has illustrated one means of contract co-ordination employed by a company that has experience of 'turnkey' contracts in many parts of the world. The diverse requirements of the contract, the high locally manufactured content, and the long distance between prime contractor and customer indicated that best co-ordination would be obtained by appointing two Project Managers, one in the United Kingdom and the other in Australia, with equal general authority but each with overriding authority in his own sphere of activities. This, in conjunction with the tightly knit communications complex between all teams, ensured smooth continuity from the Invitation to Tender stage to the hand over of the complete system to the A.P.O.

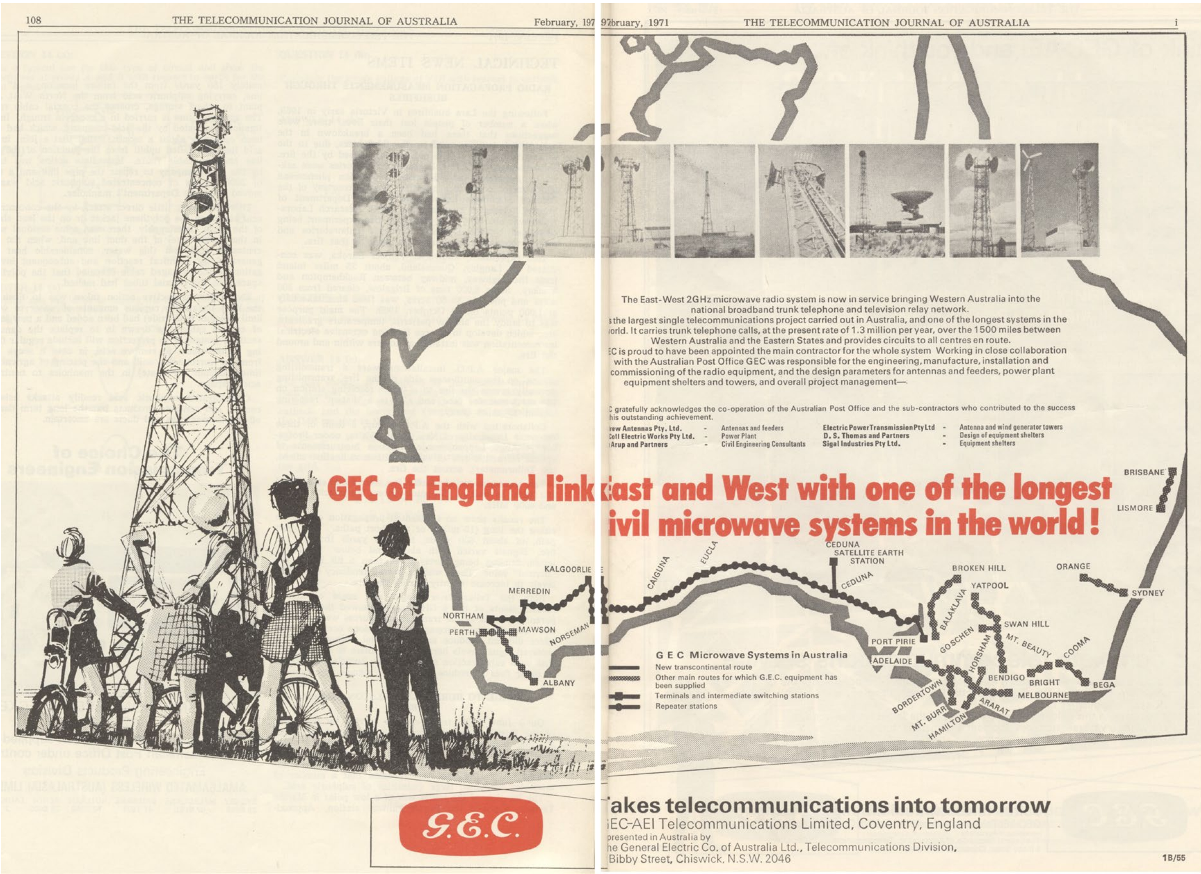

Figure 5. The GEC Australia advertisement that appeared in the TJA, *21*(1), February 1971, 108–109

The East-West Microwave Radio Relay System – Recollections

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Abstract: The revisiting of the 1971 paper, 'The Australian East-West Radio Relay System', in this issue of the *Journal* has stimulated this author to recall several of the design challenges encountered with the project in the early 1970s, and the engineering solutions achieved.

Keywords: Australian telecommunications history, East-West Radio Relay System, memoirs

The East-West Radio Relay Project

I joined the Postmaster General's Department as a Class 1 Engineer in 1970, just as the East-West Radio Relay System was entering its initial construction phase. I had the good fortune to be assigned to Radio Communications Maintenance, where I was given a free hand to observe the project and to learn everything I could about the system.

The demand for trunk connections between the cities of Australia and the regions was growing rapidly and there was an urgent need for Perth to be connected to the Eastern States, which already had a growing network of coaxial cable and microwave radio links. The East-West Radio Relay System was the beginning of addressing that demand.

It was recognised very early that there were many challenges. The distance was approximately 2,400 km through sparsely populated, inhospitable country with temperature ranges from 0°C to 50°C. The necessity for the lowest possible energy footprint drove many innovations. The 2 GHz band was chosen specifically because the available technology offered the best chance of meeting the low power requirements. It was also thought that 2 GHz would have better propagation characteristics. A trade-off was that the number of voice channels that could be carried per bearer was limited to 600, compared with 960 for a 4 GHz system at the time.

Some meteorological tests undertaken in the feasibility stage by the Telecom Research Laboratories showed that there were potential radio propagation problems arising from the

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interface of dry air from the continent and moist air from the Great Australian Bight where the route followed the coastline. It was thought that switched space diversity on selected paths and the backup standby bearer would deal with all but the worst events.

All solid-state electronics meant lower energy demand but also lower transmitter power. Low loss preformed elliptical waveguides offset this disadvantage. Equipment shelters were designed to be passively cooled involving a thin-skinned inner shelter, shaded by an insulated outer shelter with natural convection cooling between the two.

Power was to be provided by wind generators charging lead-acid batteries through a deep charge/discharge cycle. This avoided the common telephone exchange battery problem of excessive hysteresis, which could result in the complete loss of backup power — but it did require special plate design to minimise gassing and to extend the battery life.

With all of these innovations, things were bound to go wrong.

On the first section between Port Pirie and Ceduna, the preformed waveguides were found to be significantly out of spec. Fortunately, the sub-contractor, Andrew Antennas, accepted full responsibility without dispute and replaced them all at their own expense. This level of customer support was a winner for Andrew Antennas and contributed to Andrew became the supplier of choice for microwave antennas for decades.

The solid-state power amplifiers proved to be unstable and had to be reworked in the field to achieve the required group delay to support 600 voice channels. The equipment shelves had a roll-up plastic connector to the backplane running the full width of each shelf. The heat generated by the equipment caused these to delaminate and so a replacement design was introduced.

Amongst the first things to fail were the wind generators. Whether this was a design problem or a lack of understanding of the stresses is not known. The wind generators were abandoned, and power had to be provided by the local generators refuelled by tankers. This was a major lost opportunity for the PMG, which could have led the way in both wind and solar power generation.

The radio propagation problems also proved to be much more severe than anticipated. As weather patterns moved from West to East, moist air from the Great Australian Bight rolled under the dry air from the continent creating a non-linear refractive index profile, which trapped the radio signals causing rapid loss of signal level to the microwave receivers. Neither space diversity switching nor standby bearer switching could keep up with the changes. This might last half an hour on one path and then move on to the next, often causing several hours of severe disruption to the route.

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At this time, the Murdoch press was hiring a 2 Mbit/s data link on the route at night to print *The Australian* newspaper locally in Western Australia. You can imagine the pressure.

A few years later a test path was set up between Wigunda and Yangoonabie (about 40 km) using a 6 GHz 1800 channel system with phased combination space diversity. The tower heights were increased, and the 6 GHz antennas were located above the 2 GHz antennas, contrary to the standard design rules. This combination proved able to overcome the problem. The provision of the 6 GHz system was accelerated with increased tower heights and space diversity provided on all paths.

The passively cooled shelters proved to be very successful. They became a model for some major projects in the future, such as the Dampier to Perth pipeline communications system. The shelters were designed by the Telecom Structural Engineering Group and were prefabricated in a Perth factory before being trucked directly to site.

Contractual Implications

Under the terms of the contract, the delays meant that GEC would be liable for liquidated damages of some $600K ($8.6M today). GEC protested this but, after high-level negotiations, they paid the liquidated damages but received an equivalent amount in return for a series of reports which were of questionable value.

This was an unfortunate outcome, which undermined trust between the organisations. In fact, GEC did address all the problems within its control except for the wind generators; and the PMG chose not to pursue this. The radio propagation issues were by far the most serious problem, but they were not within the control of GEC.

Concluding Remarks

Despite the many challenges, the project was undoubtedly a great step forward and paved the way for a high capacity 6 GHz system which was largely free of radio propagation problems, and which was expanded as required to meet demand for many years.

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Special Issue

Emerging Technologies and Innovation for Digital Economy and Transformation

Editorial

Emerging Technologies and Innovation for Digital Economy and Transformation

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Abstract: This editorial is organized into three parts, providing a panoramic understanding of the multifaceted dimensions of digital economy and transformation. It opens with an introduction discussing the dynamic changes within the digital economy, highlighting the pivotal role of technologies and innovation as driving forces for the digital economy and transformation. It then offers insights into the selected papers and highlights the main themes explored. The third section underscores the significance of digital technologies and innovation, emphasizing their emergence as a burgeoning multidisciplinary research field. The editorial concludes by emphasizing the importance of recognizing diversity in digital transformation, and expressing gratitude to the primary contributors who shaped this special issue.

Keywords: Digital transformation, Internet of Things, Data analytics, Social media marketing, Digital finance

The Evolving Landscape of the Digital Economy

In recent years, the digital landscape has witnessed unprecedented growth: as of 2024, recent data reveals the dynamic evolution of the global digital economy, affirming its pivotal role in

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shaping the trajectory of societies and economies (Edge Middle East, 2023). The Secretary-General of the Digital Cooperation Organization (DCO) anticipates substantial growth in the digital economy, with a projected 30% contribution to global GDP by 2030, indicating a rapid acceleration in its influence on economic activities (Edge Middle East, 2023).

Following the COVID-19 pandemic, digital adoption continues to surge, with businesses and consumers increasingly relying on digital platforms. According to the International Data Corporation (IDC), worldwide spending on digital transformation is expected to reach nearly $3.9 trillion in 2027 (IDC Media Center, 2023). Moreover, a report by Statista (2024) shows the global sales in retail e-commerce totalled an estimated 5.8 trillion US dollars in 2023, highlighting the significance of digital platforms in facilitating global trade and transforming traditional business models (Statista, 2024). Additionally, the International Telecommunication Union (ITU) reveals over 5.4 billion global Internet users in 2023 (ITU-D Statistics, 2024), demonstrating the influence of digital connectivity in daily lives worldwide.

Indeed, the convergence of emerging technologies like artificial intelligence (AI), blockchain, the Internet of Things (IoT), and quantum computing has introduced new possibilities, reshaping industries, and societies.

Presently, AI is one of the top technological innovations, with expected global spending of $554.3 billion by 2024 (IDC Media Center, 2023). AI's transformative potential is evident across domains, from enhancing business processes to revolutionizing healthcare and education. Furthermore, recent AI developments have enabled a new era for scientific research. AI can process vast datasets of scientific articles, extracting knowledge through advanced tools like topic modelling, bibliometric analysis, and network visualization (Chebil *et al.*, 2021, 2024; Koubaa El Euch & Ben Said, 2024). This paradigm shift enables more efficient and effective scientific inquiry, pioneering a new age of high-performance research.

Likewise, blockchain continues to gain prominence across sectors. The global blockchain market is projected to surpass $39 billion by 2025, driven by supply chain, finance, and decentralized application uses (Statista, 2023b). Blockchain's decentralized and secure nature can revolutionize traditional business models and enable transparent, tamper-proof systems.

Furthermore, IoT is a major digital transformation catalyst. Projections show a substantial increase in global IoT connected devices, nearly doubling from 15.1 billion in 2020 to over 29 billion by 2030 (Statista, 2023a). IoT is transforming various sectors, like healthcare, manufacturing, and smart city development, enabling unparalleled insights and operational efficiencies.

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In This Issue

Following the 8th International Conference on Digital Economy (ICDEc), held in Braga, Portugal, in 2023, a call for papers was extended to all conference attendees and members of the ICDEc community to contribute to a special issue on "Emerging Technologies and Innovation for Digital Economy and Transformation" in the *Journal of Telecommunications and the Digital Economy*. The ICDEc conference has served as a platform for the exchange of ideas and insights, evolving into a dynamic forum where researchers convene to discuss and explore the transformative potential of digital advances and digital transformation. Notably, the proceedings of the eight ICDEc conferences have been documented in the LNBIP Springer books titled *Digital Economy: Emerging Technologies and Business Innovation* (Bach Tobji *et al.*, 2018, 2020, 2022; Jallouli *et al.*, 2016, 2017, 2019, 2021, 2023). Building upon the success of its predecessors, the ninth ICDEc is scheduled to take place at the Faculty of Juridical, Economic and Social Sciences (FSJES — Souissi), Mohammed V University, Rabat, Morocco, 9-11 May 2024.

This special issue represents the second collaborative project between the *Journal* and the conference series, highlighting a dedication to fostering a vibrant and interconnected community of researchers, practitioners, and enthusiasts in the domain of emerging technologies and innovation for the digital economy and transformation. The inaugural special issue, titled "Digital Technologies and Innovation" was published in June 2022, with its editorial outlining the progression of collaboration between the *Journal* and ICDEc (Jallouli *et al.*, 2022).

The call for papers challenged researchers from the fields of Computer Science, Economics, and Management to submit papers addressing topics related to the digital economy and transformation, emerging technologies, and innovation. The response was overwhelming, with a plethora of insightful papers meeting at the intersection of Information Systems, Management Innovation, and the Digital Economy. The *Journal* received 65 submissions, and the evaluation process led to the acceptance of 23 papers, yielding a selection rate of 35%.

Entitled "Emerging Technologies and Innovation for Digital Economy and Transformation", this special issue offers a selection of papers that explore the profound impact of digital transformation across diverse contexts and technologies. It provides a panoramic understanding of the wide-ranging implications of emerging technologies and covers a variety of topics, ranging from the examination of digital business models to the intricate landscape of technology adoption. It also addresses challenges in IoT technologies, blockchain technology, AI, and data analytics.

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The selected papers for this special issue have been organized into six sections based on their thematic relevance. This classification aims to assist the reader in identifying papers according to their areas of interest: (1) Digital Transformation: A Global Imperative; (2) Technology Acceptance and Adoption; (3) IoT Technologies; (4) Natural Language Processing (NLP) for Marketing Research; (5) AI for Marketing Strategies and Customer Social Media Data Analytics; and (6) Digital Finance. Each section is designed to provide variety and depth within the respective subjects, offering readers an exploration of the multifaceted dimensions of digital transformation and innovation.

Digital Transformation: A Global Imperative

The first section featured in this special issue investigates the intricacies and implications of digital transformation. The contributions explore various facets, from examining success factors for business models in value networks, to investigating barriers to digital transformation across countries. Each paper provides a distinct perspective to help comprehend the evolving dynamics of the digital economy.

The papers in the Digital Transformation theme discuss the critical factors influencing success in digitalized business models and value networks. Herrmann *et al.* (2024) and Mehmood & Hussain (2024) present systematic reviews and cross-country evidence, contributing to our understanding of value co-creation and the role of Information and Communication Technologies (ICT) in societal well-being.

Additionally, Packmohr *et al.* (2024) examine socio-demographic factors influencing barriers to digital transformation and propose countermeasures. Budiarto & Nordin (2024) offer insights into strategies for overcoming obstacles in developing countries through a literature review on technology transformation and innovation.

Furthermore, Promsa-ad & Kittiphattanabawon (2024) and Maltese (2024) contribute articles focusing on practical applications of digital transformation: Promsa-ad & Kittiphattanabawon (2024) utilize clustering techniques to identify business activity patterns related to digital transformation in transport and logistics sectors. Maltese (2024) explores challenges and opportunities of digital transformation in universities, emphasizing effective data governance and trust-building strategies.

Insights from Mahboub & Sadok (2024) and Rodríguez Ruiz *et al.* (2024) shed light on the barriers and drivers of digital transformation in different economic contexts, namely Morocco and Mexico, emphasizing the global relevance of these discussions.

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Additionally, Edquist (2024) provides a unique perspective by examining the importance of mobile broadband latency for total factor productivity growth, providing a nuanced view of the impact of technology on economic development.

Technology Acceptance and Adoption

The Technology Adoption theme explores the nuances of adopting emerging technologies, focusing on factors influencing acceptance and adoption. Ennajeh & Najar (2024) investigate blockchain adoption through the Unified Theory of Acceptance and Use of Technology (UTAUT) model, while Saklani & Kala (2024) delve into the perception of Generation Z towards chatbots, highlighting the importance of cultural context in technology acceptance.

Khemiri & Jallouli (2024) and Rahayu *et al.* (2024) contribute to our understanding of technology adoption and acceptance in financial services: Khemiri & Jallouli (2024) investigate the impact of technology-based personalization on the adoption of mobile banking services through an experimental study, shedding light on the effectiveness of personalized approaches in driving adoption. Meanwhile, Rahayu *et al.* (2024) explore determinant factors influencing the acceptance of Islamic financial technology in Indonesia, providing valuable insights into the unique socio-economic context of technology adoption in Islamic finance.

The contribution by Jabado & Jallouli (2024) provides an empirical study on the impact of Data Analytics Capabilities (DAC) on the effectiveness of Customer Relationship Management (CRM) systems and business profitability in the retail industry, underlining the relevance of technology adoption in enhancing business operations.

IoT Technologies

In the realm of IoT Technologies, Bouijij & Berqia (2024) harness the power of a Deep Neural Network to accurately classify and proactively prevent phishing websites by analysing their URLs. The method is demonstrated through a smart-home use case, aiming to reinforce IoT security. Additionally, Herrera Rubio & Prieto (2024) implement a cross-platform development board for embedded IoT systems.

Natural Language Processing for Marketing Research

The NLP for Marketing Research theme features studies that leverage Natural Language Processing to detect brand hate speech (Mednini *et al.*, 2024) and cluster social media data for marketing strategies using topic modelling techniques (Chebil *et al.*, 2024). These papers highlight the evolving role of language processing in understanding and shaping marketing strategies in the digital era.

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AI for Marketing Strategies and Customer Social Media Data Analytics

Koubaa El Euch & Ben Said (2024) and Benslama & Jallouli (2024) contribute to the exploration of Marketing, AI, and Customer Social Media Data Analytics, presenting a state-of-the-art overview and an empirical study on the impact of social media data analytics on marketing strategy. These papers emphasize the importance of AI in shaping contemporary marketing practices.

Digital Finance

The Digital Finance theme features diverse perspectives, including a critical examination of Bitcoin's environmental impact (Gopane, 2024) and a novel auto-convolutional neural network (AutoCNN) model for stock market index prediction (Zouaghia *et al*., 2024).

Furthermore, Ben Abdallah *et al.* (2024) contribute insights into the development of digital financial inclusion in China's regional context, adding a unique perspective to the global discourse on digital finance.

Overall, this special issue marks a significant step in advancing our understanding of the complex interplay between emerging technologies, innovation, and the digital transformation of economies.

Global Perspectives on Digital Transformation: Bridging Divides through Knowledge

This special issue goes beyond geographical boundaries and explores the universal themes shaping our digital future. The insights presented within these pages serve as a solid foundation for understanding the intricate dynamics of the global digital economy. The primary goal is to shed light on the multifaceted impacts of digital technologies on both the global economy and societal transformation, highlighting the necessity for collaborative efforts to navigate its complexities.

Additionally, readers are offered a unique blend of perspectives from developed and developing/emerging economies alike. While countries such as Germany, Italy, and Sweden provide insights from their advanced digital landscapes, contributions from nations such as Indonesia, India, Tunisia, and Morocco offer invaluable perspectives on the challenges encountered at different stages of digital evolution. The diverse challenges faced by countries at various stages of development enrich our understanding, while highlighting the global impact and interconnectedness of the digital economy. By fostering international dialogue, this special issue aims to contribute to a comprehensive and inclusive approach to global

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transformation. More importantly, contributions to this special issue provide a significant step forward in our understanding of the interplay between emerging technologies, innovation, and the digital transformation of economies.

Lastly, we extend our sincere appreciation to the authors, reviewers, and editorial team for their dedicated contributions to this endeavour. More specifically, the successful completion of this issue is greatly credited to the collaborative efforts and unwavering support provided by Professor Leith Campbell, the Managing Editor of this *Journal*. The guest editors, representing the broader ICDEc community, extend heartfelt appreciation for his invaluable guidance throughout the entire production process. Indeed, Professor Campbell's insights and expertise significantly contributed to the meticulous evaluation and enhancement of the content featured in this issue. The collaborative synergy with the guest editors confirms a shared commitment to upholding high standards of scholarly excellence within this special edition. Looking ahead, plans for additional joint projects and special issues in partnership between the *Journal* and ICDEc are anticipated.

In conclusion, the complex and dynamic landscape of emerging technologies reminds us of the necessity for a global collaboration, dialogue, and ethical considerations. This special issue serves as a platform for exchanging ideas and the cultivation of knowledge, guiding us toward a future where digital innovation is leveraged for the benefit of societies. We truly hope that this compilation will inspire further exploration, innovation, and dialogue on the transformative impact of emerging technologies in the digital age.

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Value Co-creation in a Digitalised and Dematerialised World

Critical Factors Contributing to Success or Failure of Business Models in Value Networks

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Abstract: Due to increased digitalisation and dematerialisation, the traditional value chain concept appears to be outdated. Instead, the term value network has emerged to describe how organisations co-create value in today's economy. However, it remains unclear what contributes to success or failure of collaborative business models in value networks. The article closes this research gap. The authors identify relevant papers through a systematic literature review process and review them using qualitative content analysis. From the 45 papers analysed, 21 critical factors contributing to success or failure of business models in value networks were extracted. They can be structured along 6 dimensions. From a theoretical perspective, the article deepens the understanding of business models in value networks and provides clear perspectives for future research. From a practical perspective, managers can use the results as target variables for strategic management to ensure success of their value network.

Keywords: business model, value network, systematic literature review, success factors, failure factors

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Introduction

Digitalisation and dematerialisation have fundamentally changed the way in which organisations create and capture value (Ricciotti, 2020). To succeed in today's economy, businesses are moving away from product-centric value propositions, leaning more and more towards providing innovative services and solutions that rely heavily on digital technologies (Kindström, 2010). Economic value is increasingly created through the exchange of knowledge and intangible benefits, rather than transactions around goods, services and revenue alone (Wild, 2009). Subsequently, instead of operating in a sequential and linear logic of value creation as implied by the traditional value chain concept (Porter, 1985), organisations need to transform their business models to co-create value in a networked manner (Rachinger *et al.*, 2019).

However, it remains unclear which target variables are critical to ensure competitive success in such a value network (Ricciotti, 2020). Existing research is insufficient to answer this question: first, because authors integrate the concept of value networks in their studies without elaborating on the implications that the differing organisational context might have on business practices (e.g., Centobelli *et al.*, 2020; Pies & Schultz, 2023); secondly, because existing research is fragmented. Several case studies are focused on describing particular value networks in terms of business model, composition, roles and activities (e.g., Mair & Schoen, 2007). However, these empirical findings have yet to be condensed to higher-level patterns. While systematic reviews of the research landscape on the co-creation of value in networks exist, they are limited to more conceptual aspects (Jocevski *et al.*, 2020; Ricciotti, 2020). In sum, there is a need for a systematic overview of factors contributing to success or failure of businesses cooperating in value networks. By conducting a qualitative content analysis on papers identified using a systematic literature review process, this study closes this gap by answering the following research question:

RQ: What are critical factors contributing to success or failure of business models in value networks?

Our paper contributes to theory and practice alike. From a theoretical perspective, researchers will benefit from a structured analysis of critical factors contributing to success or failure of business models in value networks, which previously did not exist in the literature. The overview and analysis can guide future research in the field. From a practical perspective, managers can use the information derived as target variables for strategic management to ensure success of their value network (Rockart, 1979).

The remainder of the study is organised as follows. Section 2 will introduce the theoretical foundation central to our study. Section 3 will outline in detail our research approach. Section

4 will report the results of our analysis. Section 5 will discuss the findings, directions for future research and limitations of the study.

Theoretical Foundation

As our paper aims to extract critical factors contributing to success or failure of business models in value networks, the following chapter is dedicated to introducing the concepts central to this research question.

First, a value network can be defined as any web of relationships generating tangible and intangible value based on complex dynamic exchanges between two or more network participants, such as individuals, groups or organisations (Allee, 2000). While there exists no structured analysis of the specific differences of businesses operating in a value network as opposed to a value chain, several aspects stand out from the literature. In a value network, value is not created in a linear manner as was the case for many industrial-age business models that followed clearly fleshed out supply chains. Rather, value is co-created in a cooperation of different organisations, whose goal it is to jointly add value for the end user or customer (Kartseva *et al.*, 2004). The end-product or service defines the market for the entire value network (Allee, 2000). Subsequently, business models of organisations operating in a value network are interconnected and interplaying to deliver the joint value proposition (Ghezzi, 2013). The constellation of actors and their interaction is in constant flux, rather than in static linear chains. While tangible goods continue to be exchanged, in particular the exchange of intangible goods contributes to joint value creation (Allee, 2008) .

Secondly, a business model describes how organisations create, deliver, and capture value, whether economic, social, or of some other form (Osterwalder, 2004). The concept can be used to understand and define the underlying core logic and strategic choices of value creation (Shafer *et al.*, 2005). Historically, authors typically referred to a single organisation when describing a business model (Jocevski *et al.*, 2020). Other organisations were included in the analysis but considered as partners for delivering a firm-centric value proposition (e.g., in the role of a supplier). In light of the previous section on the key aspects of value creation in value networks, it becomes apparent that the business model concept must be expanded in order to capture the aspect of value co-creation in the sense of an interorganisational value proposition. Jocevski *et al.* (2020) suggest four questions to describe a network-oriented business model: who (referring to the actors that are interconnected through the business model and their orchestration); what (referring to the joint value proposition); how (referring to the value flow and activities needed to deliver the joint value proposition); and why (referring to reasons and practices behind the utilization of the value network). However, the implications on managerial practices of this network-oriented view on business models remain unclear. The authors suggest a more in-depth analysis that goes beyond empirical examples and case studies to deepen the understanding of networked business models.

To meet this need, and in order to support theory and practice alike, we chose to investigate critical factors contributing to success or failure of business models in value networks. The concept of success factors was first introduced by Bullen & Rockart (1981). They can be defined as "the limited number of areas in which satisfactory results ensure successful competitive performance" for an organisation. The concept has established itself in the management literature in various contexts for practical research (Rohn *et al.*, 2021; Trkman, 2010). However, other authors also suggest to study challenges or failure factors (Özcan *et al.*, 2022). These are also critical because, if not considered, they may lead to partial maldevelopment or complete failure of an organisation (Gargeya & Brady, 2005). We agree with Taherdoost & Keshavarzsaleh (2016) that success factors and failure factors can be considered two sides of the same coin. Therefore, we choose the term critical factors in order to indicate the ambivalence of the factors identified, namely that they can play a decisive role in both success and failure of business models in value networks.

Research Approach

We followed two steps to identify critical factors contributing to success or failure of business models in value networks. First, we followed a systematic literature review process to identify papers that cover business models in value networks. Secondly, these papers were analysed using a qualitative content analysis to answer our research question. The combination of these methods is established (e.g., Centobelli *et al.*, 2020; Hanelt *et al.*, 2021) and has also been used to extract critical success factors from the literature (e.g., Hietschold *et al.*, 2014; Medeiros *et al.*, 2022). Both steps are described in detail below.

Identification of relevant literature

We conducted a systematic literature review process to identify literature relevant to answer our research question, following established recommendations for this methodology (Tranfield *et al.*, 2003; Webster & Watson, 2002). Figure 1 depicts the flow chart of the different steps conducted, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting guidelines (Page *et al.*, 2021).

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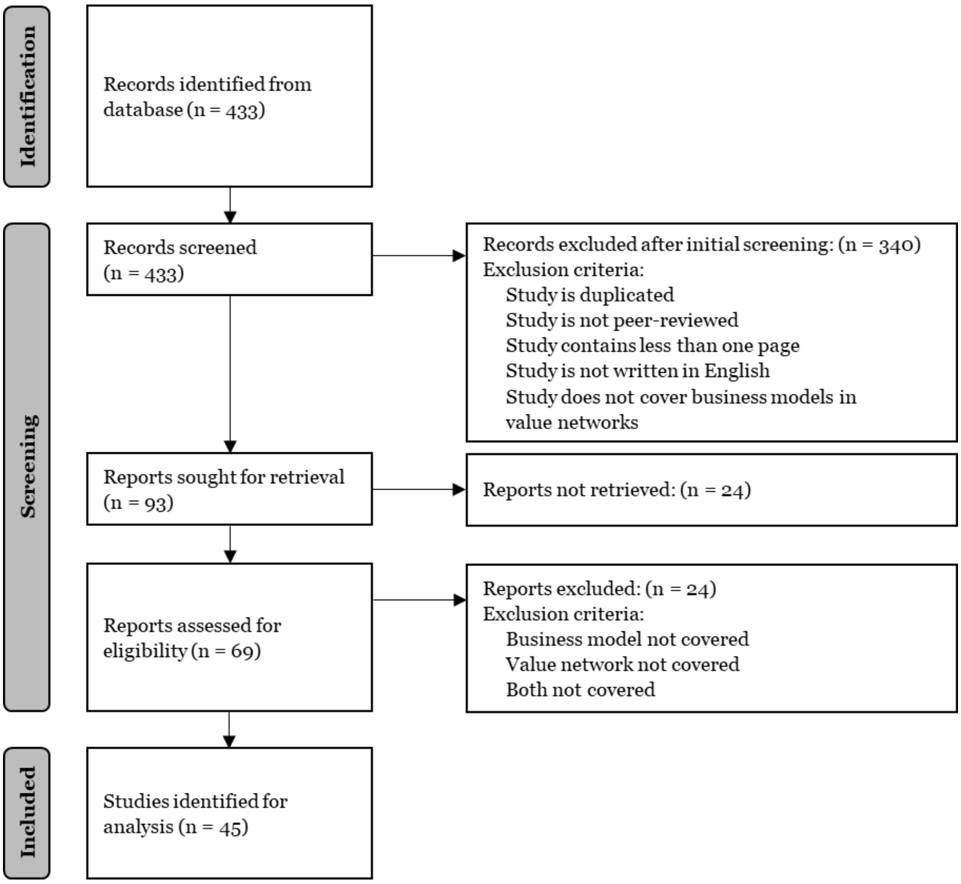

Figure 1. Flow diagram of systematic literature review process

In the identification phase, we undertook a keyword search in Scopus in April 2023 to collect relevant literature. We conducted separate queries for "value network" and "business model" in singular or plural in article title, abstract and keywords. We combined both queries with the Boolean operator AND, yielding 443 results eligible for further analysis (see Table 1).

Table 1. Number of studies by search string

	Scopus
#1 "value network" OR "value networks"	1,993
#2 "business model" OR "business models"	44,052
TOTAL (#1 AND #2)	**443**

For the screening process, we defined five exclusion criteria. First, the study is duplicated. Second, the study is not peer-reviewed (e.g., presentation slides, extended abstracts, invited papers, keynote speech, workshop reports, book chapters). Third, the study contains less than one page. Fourth, the study is not written in English. Fifth, the study does not present any type of findings or discussion about business models in value networks. In an initial screening step, we focused on screening the abstracts of the papers, applying the exclusion criteria. Subsequently, 93 records were sought for retrieval of which 24 could not be retrieved. A full-text screening was conducted with the remaining 69 reports. In this step, we were able to more thoroughly assess whether the concepts "business model" and "value networks" were covered

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in the article. All screening steps were conducted by at least two reviewers to ensure quality and reliability (Snyder, 2019). Disagreements were resolved through discussion. The procedure led to 45 papers eligible for full text analysis.

Deduction of critical factors for success or failure

To extract critical factors contributing to success or failure of business models in value networks, we conducted a qualitative content analysis (Mayring, 2000). Qualitative content analysis has been steadily used in business research (Neuendorf, 2002). It is an established methodology to condense existing knowledge about a phenomenon into categories (Krippendorff, 1980) and thus suitable to answer our research question. We followed a deductive approach in three phases, as outlined by Elo & Kyngäs (2008) (see Figure 2).

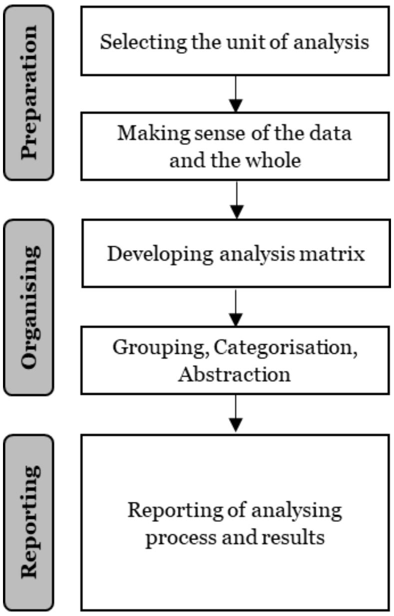

Figure 2. Deductive qualitative content analysis process

In the preparation phase, the unit of analysis was selected as the 45 papers identified through our systematic literature review process outlined before. To make sense of the data, the researchers conducted several high-level analyses to better understand the papers in scope. This included extracting the general theme of the papers, research strategy (conceptual vs empirical), the definitions adopted for value network and business model, and getting an initial sense if factors contributing to success or failure of business models in value networks are present.

As we have already made sure through our selection process that all papers cover business models in value networks, our analysis routine in the organising phase only needed to ensure we extract critical factors contributing to success or failure from the papers. To achieve that, we applied the definitions outlined in the previous chapter to our coding protocol: success factors were defined as areas in which satisfactory results ensure successful competitive performance of the value network; while failure factors were defined as factors that may lead to partial maldevelopment or complete failure of a value network. Coding was conducted using the software MAXQDA; relevant text passages were coded as either success or failure factor. At least two reviewers assessed every paper. This resulted in a list of quotes that were grouped as being either a success or failure factor for business models in value networks. To come up with more abstract critical factors, we assigned a sub-category to each quote that closely mirrors the original wording. These sub-categories were then summarized into higher-order categories, i.e., the critical factors of interest to answer our research question. Lastly, these categories were aggregated into abstract dimensions. Table 2 illustrates the grouping, categorisation and abstraction process deployed.

Table 2. Illustration of category formation process

Coded quote	Group	Sub-category	Category (critical factor)	Dimension
"One element of this is the need for an innovative business model to be developed that focuses on the achievement of strategic outcomes by aligning ICT [Information and communications technology] services" (Al-Debei & Fitzgerald, 2010)	Success factor	Development of innovative business model that focuses on strategic outcomes based on aligned services	Business model design for value network	Cooperative business practices
"Different firms usually participate with firm-centric BMs [business models] that could be in mutual conflict" (Jocevski *et al.*, 2020)	Failure factor	Firm-centric business models that could be in mutual conflict		
…	…	…		
"Investments sometimes are too large or involve too high risks set in relation to the returns" (Ek *et al.*, 2022)	Failure factor	Too large/risky investments in relation to return	Alignment and understanding of finances (revenue, cost, investment agendas)	
"Unclear and unbalanced distribution of costs and benefits, since often most of the benefits are not received by the actors making the largest portion of the investment" (Ghanbari *et al.*, 2017)	Failure factor	Unclear and unbalanced distribution of costs and benefits		
…		…		

Table 3. Overview of papers identified for analysis

Source	Theme	Research strategy	Definition of value network/business model provided?	Success/failure factors coded?
Al-Debei *et al.* (2013)	Design of a value network model for creating innovative mobile data services	Empirical	Yes/No	Yes
Al-Debei & Fitzgerald (2010)	Development of a business model ontology for mobile data services	Empirical	Yes/Yes	Yes
Alves & Roque (2005)	Mapping of value nets to analyse business models of Massively Multiplayer Online Role-Playing Games (MMORPGs)	Empirical	No/Yes	-
Baumöl & Winter (2001)	Analysis of impact of IT potentials on value-added networks and the organisational innovation related to it	Conceptual	Yes/No	Yes
Brehmer *et al.* (2018)	Analysis of business models of innovative sustainable organisations in the Netherlands	Empirical	No/Yes	-
Breuer *et al.* (2015)	Analysis of location-based services in terms of business model and value network with focus on user data	Conceptual	Yes/No	Yes
Camps-Aragó *et al.* (2021)	Analysis of monetisation strategies for cooperative intelligent transport systems	Conceptual	No/No	Yes
Capo *et al.* (2014)	Analysis on how business models can complement each other in a value network and survive an industry crisis	Empirical	No/Yes	Yes
Cavallo *et al.* (2021)	Combination of strategic network and value network, impact of the network on participants and vice-versa	Conceptual	Yes/Yes	Yes
Costa & Da Cunha (2009)	Combination of business modelling and actor-network theory	Conceptual	No/No	-
Costa & Da Cunha (2015a)	Combination of business modelling and actor-network theory	Conceptual	No/No	Yes
Costa & Da Cunha (2015b)	Combination of business modelling and actor-network theory with focus on social dimension of business models	Conceptual	No/No	-
Darzanos *et al.* (2022)	Evaluation of business model for 5G-experimental environments	Conceptual	No/No	-
Darzanos *et al.* (2023)	Introduction of a framework for 5G-business model assessment	Empirical	No/No	-
Dellyana *et al.* (2018)	Analysis of business model innovation to support multi-dimensional value networks	Empirical	Yes/Yes	Yes
Derks et al. (2022)	Proposition of a collaborative sustainable business modelling approach to achieve transition to more sustainability	Empirical	Yes/Yes	Yes
Eaton *et al.* (2010)	Analysis of value network and control points as a valid methodology to identify profitable business models for the mobile telecoms industry	Conceptual	Yes/Yes	-

Source	Theme	Research strategy	Definition of value network/business model provided?	Success/failure factors coded?
Ek *et al.* (2022)	Design, reconfiguration and development of Green Symbiosis Business Value Networks (GSBVNs)	Conceptual	Yes/No	Yes
Fjeldstad & Snow (2018)	Proposition of value configuration as a business model contingency variable which affects the properties of business model elements	Conceptual	Yes/Yes	Yes
Gao & Krogstie (2015)	Analysis of business models of mobile ecosystems in China	Empirical	Yes/Yes	Yes
Gao & Zhang (2016)	Analysis of business models of sharing economy in China	Empirical	Yes/Yes	Yes
Ghanbari *et al.* (2017)	Analysis of vertical, cooperative business models in the Internet of Things (IoT)	Empirical	Yes/Yes	Yes
Ghezzi (2013)	Proposition of a framework for business models, value networks and resource management as a tool to identify discontinuous phenomena and trigger strategic re-planning	Empirical	Yes/Yes	-
Ghezzi *et al.* (2013)	Proposition of a methodological framework for developing innovative interconnection business models	Empirical	Yes/Yes	-
Granjo *et al.* (2014)	Mapping of different business modelling perspectives based on ontologies	Empirical	Yes/No	-
Guo *et al.* (2013)	Investigation of top managers' human and social capital on business model innovation by adopting a value network-based definition for business models	Empirical	Yes/No	Yes
Hung *et al.* (2010)	Combination of business values (value chain, value shop, value network) and design of an organic farming system	Empirical	Yes/No	Yes
Jocevski *et al.* (2020)	Literature review on interconnected business models	Conceptual	Yes/Yes	Yes
Nieuwenhuis & Kijl (2010)	Proposal of an early-stage business model and value network development approach for an e-health service in the research and development phase	Empirical	No/Yes	-
Kytölä *et al.* (2011)	Analysis of dynamic nature of the business model concept and illustration of its key elements within a healthcare supply chain	Empirical	No/Yes	Yes
Leviäkangas & Öörni (2020)	Exploration of relationship between business models, value chains and business ecosystems with a meta-model for transport-related services	Conceptual	Yes/Yes	Yes
Li & Whalley (2002)	Transformation from value chains to value networks in telecommunication industry	Conceptual	Yes/Yes	Yes
Lindman *et al.* (2014)	Investigation on emerging open data value network structure based on empirical findings from 14 Finnish organisations	Empirical	No/Yes	Yes

Source	Theme	Research strategy	Definition of value network/business model provided?	Success/failure factors coded?
Mair & Schoen (2007)	Analysis of social entrepreneurial organisations which managed to achieve scale and sustainability in developing economies	Empirical	No/Yes	Yes
Moro & Cauchick-Miguel (2022)	Analysis of a bike-sharing system implemented in the south of Brazil from business model perspective by focussing on the value network	Empirical	No/No	Yes
Nieuwenhuis & Kijl (2010)	Proposition of a business model engineering approach for the introduction of telemedicine services	Empirical	No/Yes	Yes
Reinhold *et al.* (2022)	Proposition of a value creation framework and roles for smart services within the manufacturing industry	Conceptual	Yes/No	Yes
Rezazadeh & Carvalho (2017)	Identification of business model innovation types	Conceptual	Yes/Yes	Yes
Riasanow *et al.* (2017)	Visualisation of the current automotive ecosystem, by evolving a generic value network using the E3 method	Empirical	Yes/No	Yes
Roelens & Poels (2013)	Identification of strategic elements of the Value Delivery Modelling Language (VDML) meta model	Conceptual	Yes/No	-
Spruytte *et al.* (2017)	Definition of the concept of dynamic value network configurations	Conceptual	Yes/No	Yes
Stanoevska-Slabeva & Fricke (2015)	Proposition of a design procedure and an overview of design options for development of inter-organisational business models for composite software products	Conceptual	Yes/No	Yes
Suherman & Simatupang (2017)	Proposition of an ontology and a concept for cloud-computing based business models	Conceptual	Yes/No	Yes
Tian *et al.* (2008)	Proposition of a framework for the modelling and analysis of business model designs involving a network of interconnected business entities	Conceptual	Yes/Yes	Yes
Wu *et al.* (2012)	Redefinition of the concept of business model and proposition of an analytical framework of business model from the perspective of value network	Conceptual	No/Yes	Yes

Findings

Table 3 shows the 45 studies identified for analysis through our systematic literature review process, as well as the information gathered through our preparation process of our qualitative content analysis. In line with existing literature (Ricciotti, 2020), our sample shows that business models in value networks have been studied for quite some time, as the studies date from 2001 to 2022. The studies pursue a conceptual and an empirical approach in equal measure (23 empirical, 22 conceptual papers). Although (by definition of our search procedure) all papers utilise the terms “value network” and “business model”, not all of them provide definitions for the concepts. Out of the 45 papers, 29 papers provide a definition for value network (64%), while 25 provide a definition for business model (55%). The definitions adopted vary. For value network, the definition mostly adopted is the one by Allee (2000) also adopted in our study. For business model, the definitions mostly refer to Chesbrough & Rosenbloom (2002), which emphasizes the role of technical innovation to create and capture value. Regarding the general theme of the papers, it can be observed that the research domain varies – while most papers are grounded in an ICT context, others are also taking place in a sustainability context.

Regarding our research question, we identified 33 papers to be relevant for coding of critical factors contributing to success or failure of business models in value networks. From these papers, we were able to code 172 quotes using our coding protocol. Based on this total number of quotes, 108 were grouped as success factors, 64 as failure factors. Applying the categorisation and abstraction process outlined in the previous section, we were able to extract 21 critical factors contributing to success or failure of business models in value networks. We consider success and failure factors to be two sides of the same coin (Taherdoost & Keshavarzsaleh, 2016), allowing us to aggregate them to overarching factors. Still preserving the initial grouping of the quote as a success or failure factor allows us to maintain the context in which it is discussed in the literature. Abstracting the critical factors further, they can be structured along 6 dimensions. Table 4 provides an overview of the findings from the qualitative content analysis regarding our research question.

Cooperative business practices is the dimension mentioned the most (33% of all mentions), followed by *Interaction between actors* (21%) and *Value network architecture* (21%). *Value network context*, *Organisational readiness,* and *Value network infrastructure* only account for a smaller share of mentions (10%, 9% and 4%, respectively). The five most mentioned critical factors contributing to success or failure of business models in value networks are: Business model design for value network (26 mentions); Definition, design and alignment of roles, activities, and competencies (18 mentions); Alignment and understanding of finances (revenue, cost, investment agendas; 14 mentions); Adapted product development that includes customers (13 mentions); Dynamic character of network (11 mentions); Human resources readiness (i.e., availability of employees and leadership with required skillset; 11 mentions). We will continue to describe the dimensions and associated factors in more detail below.

Table 4. Results of qualitative content analysis regarding our research question

Dimension	Critical factor for success or failure of business models in value networks	Number of Mentions		
		Success factor	Failure factor	Total
Cooperative business practices	Business model design for value network	15	11	26
	Alignment and understanding of finances (revenue, cost, investment agendas)	2	12	14
	Adapted product development that includes customers	10	3	13
	Feasibility assessment and piloting	3	0	3
Interaction between actors	Dynamic character of network	3	8	11
	Active engagement of actors	5	4	9
	Cooperative data management (collection, sharing, analysis)	6	3	9
	Active management of communication	5	3	8
	Relationship management within value network	4	0	4
Value network architecture	Definition, design and alignment of roles, activities, and competencies	16	2	18
	Inclusion of relevant players	8	2	10
	Long-term strategies, agreements, and contracts within value network	4	1	5
	Openness of value network	3	0	3
Value network context	Favourable regulations	2	6	8
	Relationship management with government	4	0	4
	Understanding of institutional factors and conditions	2	1	3
	Competitive environment	0	2	2
Organisational readiness	Human resources readiness (i.e., availability of employees and leadership with required skillset)	7	4	11
	Organisational readiness for collaboration (in terms of infrastructure and capacity)	3	1	4
Value network infrastructure	Efficiency of infrastructure (stability, reliability)	4	0	4
	Design of adequate infrastructure (physical / financial / technical)	2	1	3
Total	**-**	**108**	**64**	**172**

Cooperative business practices: Organisations cooperating in value networks need to adapt their business practices to align them to a shared value creation. This first and foremost includes the adaptation of the business model. An overarching value proposition needs to be defined (Derks *et al.*, 2022; Ghanbari *et al.*, 2017), tested (Nieuwenhuis & Kijl, 2010), and aligned across actors of the value network (Dellyana *et al.*, 2018; Moro & Cauchick-Miguel, 2022), as well as with partners and suppliers (Rezazadeh & Carvalho, 2017). This is a complex process (Leviäkangas & Öörni, 2020) because the business model should be designed to be attractive for each participant of the value network (Costa & Da Cunha, 2015a), while also preventing conflict between firm-centric business models (Jocevski *et al.*, 2020). The alignment of finances in a value network is often a challenge. This concerns mainly the difficulty to outline a compelling outlook regarding return on investments for all participants (Derks *et al.*, 2022; Ek *et al.*, 2022; Ghanbari *et al.*, 2017; Wu *et al.*, 2012), as well as securing the financing for the necessary investments (Camps-Aragó *et al.*, 2021; Ek *et al.*, 2022; Moro & Cauchick-Miguel, 2022). It is also essential to adapt product development for a joint value creation (Fjeldstad & Snow, 2018; Mair & Schoen, 2007) and to ensure proximity to the customer throughout (Al-Debei & Fitzgerald, 2010; Hung *et al.*, 2010; Moro & Cauchick-Miguel, 2022). Feasibility studies and pilot projects are encouraged to validate the potential of the identified synergies (Derks *et al.*, 2022; Ek *et al.*, 2022; Ghanbari *et al.*, 2017).

***Interaction between actors*:** Shared value creation in value networks also places specific demands on the interaction between participating actors. Participating organisations must have the capacity for dynamic adaptation of cooperation patterns, for example due to changes in the competitive or legal landscape or the structure of the value network (Baumöl & Winter, 2001; Dellyana *et al.*, 2018; Ghanbari *et al.*, 2017; Spruytte *et al.*, 2017). It is essential to actively involve all actors in the joint value creation process to ensure alignment and prevent isolated organisational developments (Gao & Krogstie, 2007; Reinhold *et al.*, 2022; Derks *et al.*, 2022; Capo *et al.*, 2014). As the exchange of knowledge and intangible goods is integral to value networks, businesses should also implement cooperative data management practices (Cavallo *et al.*, 2021; Lindman *et al.*, 2014). This includes assessing which (sensitive) data is essential to be shared to identify and exploit collective business opportunities (Ek *et al.*, 2022; Lindman *et al.*, 2014). The operationally high communicative demands of value networks require the design and active usage of appropriate communication channels between the relevant business roles (Costa & Da Cunha, 2015a; Dellyana *et al.*, 2018; Ek *et al.*, 2022). On a higher level, actors should also invest in a close and trustful relationship among each other that is required for cooperation (Ek *et al.*, 2022; Gao & Zhang, 2016; Stanoevska-Slabeva & Fricke, 2015).

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***Value network architecture*:** To design a successful value network architecture, organisations need to have an aligned understanding of roles, activities, and value flows (Al-Debei *et al.*, 2013; Breuer *et al.*, 2015; Capo *et al.*, 2014; Dellyana *et al.*, 2018) that ensures complementary contributions from involved actors (Jocevski *et al.*, 2020; Li & Whalley, 2002; Stanoevska-Slabeva & Fricke, 2015). Organisations should identify relevant partners to join the overarching business model and persuade them to become part of the value network to realise a diverse but synergistic network (Derks *et al.*, 2022; Li & Whalley, 2002; Moro & Cauchick-Miguel, 2022; Riasanow *et al.*, 2017). In terms of value network governance, long-term strategies, agreements, and contracts between the actors should be formulated on how to implement, finance and scale value co-creation opportunities (Derks *et al.*, 2022; Ek *et al.*, 2022). The value network structure should also be set up to be inclusive for new actors to enter (Dellyana *et al.*, 2018; Riasanow *et al.*, 2017).

***Value network context*:** The success of a value network is also dependent on external conditions. Most notably, legislation has been identified as a potent factor to affect competitive dynamics of a value network (Gao & Zhang, 2016; Kytölä *et al.*, 2011; Leviäkangas & Öörni, 2020; Tian *et al.*, 2008). While it can act both as a driving force as well as a barrier (Ek *et al.*, 2022), the dependency on favourable regulations has been identified more often as a challenge. Hence, actors of the value network should invest in a positive relationship with government officials and lobby to change the applicable legal framework (Derks *et al.*, 2022; Gao & Krogstie, 2007; Gao & Zhang, 2016). Furthermore, a deep understanding of the institutional factors and conditions surrounding and potentially impacting the value network is essential (Ek *et al.*, 2022; Leviäkangas & Öörni, 2020). Lastly, value networks often operate in extremely volatile market dynamics and thus may be subject to a rapidly changing competitive landscape (Al-Debei *et al.*, 2013; Li & Whalley, 2002).

***Organisational readiness*:** Organisations also need to be fit individually for collaboration in a value network.; first, in terms of human resources. Managers need to be equipped with entrepreneurial skills that allow them to identify opportunities in value networks, as well as managerial skills to effectively allocate appropriate resources (Al-Debei & Fitzgerald, 2010; Guo *et al.*, 2013; Kytölä *et al.*, 2011). Employees need a good understanding of the local market conditions and capabilities to cope with the dynamic nature of value networks (Gao & Krogstie, 2007; Gao & Zhang, 2016). It is important for an organisation to invest in personal development and retention measures to ensure availability of resources with the appropriate skillset (Gao & Krogstie, 2007; Gao & Zhang, 2016; Suherman & Simatupang, 2017). Secondly, organisations also need to have suitable infrastructure, effective business processes and sufficient capacity to deliver a collaborative value proposition (Al-Debei & Fitzgerald, 2010; Derks *et al.*, 2022; Wu *et al.*, 2012).

***Value network infrastructure*:** Lastly, organisations collaborating in value networks require suitable infrastructure for value co-creation. Due to the high level of interaction and exchange of value, an essential requirement for the infrastructure is to be stable and reliable. This has been found as especially important for the technological architecture of value networks (Ek *et al.*, 2022; Gao & Krogstie, 2007; Al-Debei & Fitzgerald, 2010; Suherman & Simatupang, 2017). Besides ensuring efficiency of infrastructure, the actual design of an adequate infrastructure has also been identified as a success factor. Actors in value networks should align their physical, financial, and technical infrastructure to the joint value proposition (Derks *et al.*, 2022; Ek *et al.*, 2022).

Conclusions

The paper presents critical factors contributing to success or failure of business models in value networks through combing a systematic literature review process with qualitative content analysis. We were able to identify 21 critical factors that can be structured along 6 dimensions. Both are summarized in Figure 3.

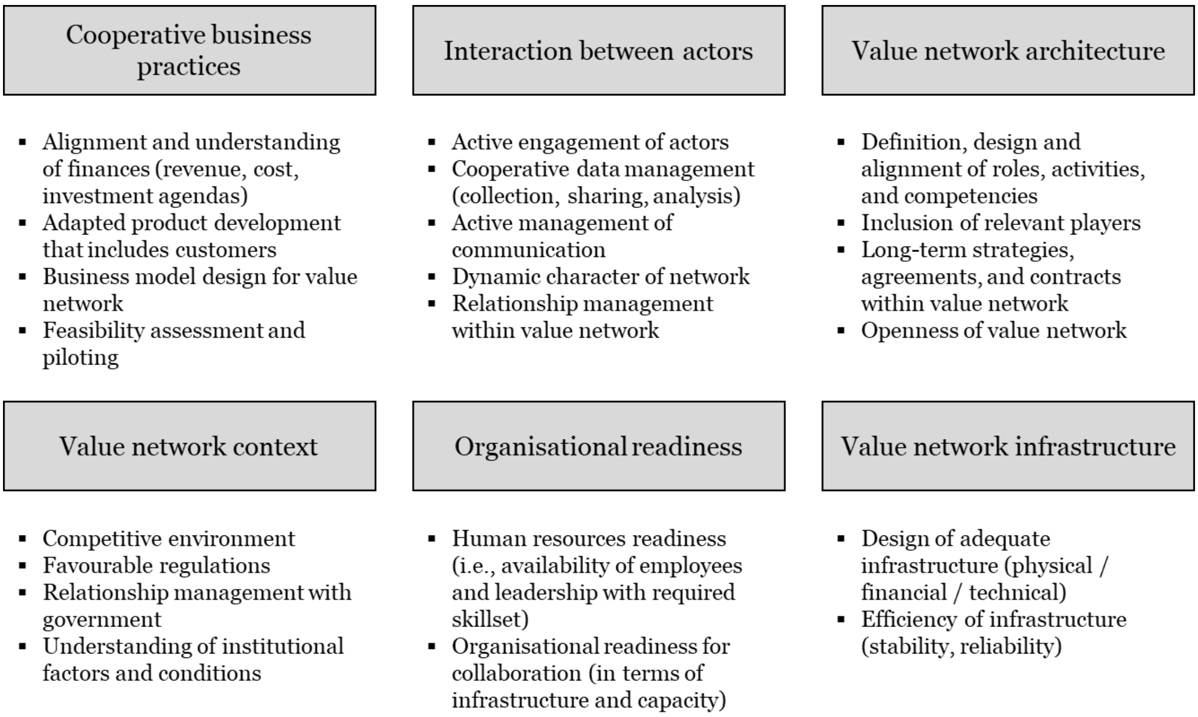

Figure 3. Overview of dimensions and critical factors contributing to success or failure of business models in value networks

Discussion of the results and implications for future research

Reviewing the reported results, several observations can be made that also lead to implications for future research. These are summarized in Table 5 and will be explained in detail below.

Table 5. Results of qualitative content analysis regarding our research question

Observation	Implication for future research
1. Number of mentions of critical factors in literature may not correspond to actual relevance in practice	Conduct quantitative studies to assess relative importance of critical factors and their actual impact on value network performance indicators
2. Reporting of critical factors qualitative – actual impact on performance indicators remains unclear	
3. Critical factors are mentioned as a by-product and not central to studies	Conduct in-depth analysis of individual critical success factors
4. Lack of managerial recommendations to ensure success of value networks	
5. Studies conducted in different contexts that might affect relevance of critical factors	Consider contextual factors in analysis (e.g., industry, business model maturity, value network maturity)

First, looking at the representation of the dimensions as well as the critical factors in the literature, one can notice an asymmetrical distribution of mentions (see Table 4). For example, the three dimensions *Cooperative business practices*, *Interaction between actors*, and *Value network architecture* account for three-quarters of all mentions, while the other three dimensions account for the remaining quarter of all mentions. Similarly, the factors *Business model design for value network* and *Definition, design, and alignment of roles, activities, and competencies* are mentioned the most in the literature, together accounting for roughly 20% of all mentions. One might be tempted to infer causal conclusion and a prioritisation from these asymmetries. For example, as critical factors from the *Value network architecture* dimension are mentioned more often than critical factors from the *Value network infrastructure* dimension, one might infer that these are more decisive for a successful business model in a value network. However, although the extracted number of mentions might be a valuable hypothesis for a prioritisation, the extent to which a certain critical factor or dimension is covered in the literature might not necessarily coincide with its actual relevance in practice. For example, if it is difficult to collect data for a given factor, it may naturally appear less often in the literature. Second, and in a similar vein, most of the papers in our analysis report critical factors for success or failure only in a qualitative manner. It thus remains unclear how large their impact on tangible performance indicators of a value network is in practice.

We thus call for future research to choose quantitative methodologies to assess the relative importance of critical factors and their actual impact on value network performance indicators. This can be achieved by conducting a survey with practitioners. This has already been done in the managerial field for critical success factors in other domains (e.g., Chow & Cao, 2008; Yusof & Aspinwall, 2000). The 21 factors identified in our study can be used as a fixed set of independent variables whose significance and influence on various dependent

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variables are analysed. In the long run, the more in-depth analyses on specific critical factors are available (see the following section), systematic literature reviews can be deployed to collect and aggregate empirical data on their individual and relative importance. Currently, this is not possible due to lack of studies reporting data that quantifies the impact of critical factors for success or failure of business models in value networks.

Third, in most of the studies in our sample, the reporting of critical factors for business models of value networks was merely a by-product. Usually, they were reported as learnings from conducting a case study (e.g., Derks *et al.*, 2022) or by citing other literature (e.g., Ek *et al.*, 2022). Fourth, both conceptual and empirical papers often remain unclear why specific factors have contributed to success or failure of a particular business model in a value network. We thus call for further research to conduct in-depth investigations of individual critical factors. Such analyses can then also derive more concrete managerial implications. We would suggest utilising the number of mentions collected through our analysis to guide a prioritisation, drawing on existing frameworks and tools and implementing them in practice. For example, for the factor *Business model design for value networks*, two papers in our sample have made contributions in outlining steps to develop an inter-organisational business model (Ghezzi, 2013; Stanoevska-Slabeva & Fricke, 2015). Similarly, authors have proposed ontologies to support implementation of the factor *Definition, design, and alignment of roles, activities, and competencies* (e.g., Al-Debei & Fitzgerald, 2010; Camps-Aragó *et al.*, 2021; Cavallo *et al.*, 2021). These methods can be applied in a case study to gain in-depth experience of their implementation. As mentioned in the previous section, this should also entail the collection of empirical data to facilitate the quantification of the impact of critical factors.

Fifth, the studies considered for our analysis were rooted in different context. For example, the studies by Derks *et al.* (2022) and Ek *et al.* (2022) took place in a sustainability setting, while the studies by Ghanbari *et al.* (2017) and Reinhold *et al.* (2022) are anchored in an ICT context. Depending on the context, the importance of critical factors on the success or failure of a value network might differ. We suggest that future research differentiates by contextual factors (e.g., industry, business model maturity, value network maturity) to further elevate our knowledge of critical factors for success or failure of business models in value networks.

Research limitations and contributions

Our study has three main limitations. First, as with any systematic literature analysis process, the selection of papers can be challenged. Specifically, it can be questioned whether our study would have benefitted from extracting literature from other databases besides Scopus. However, Scopus has been shown to have a substantial overlap with Web of Science as the other predominantly used database for bibliometric analysis (Singh *et al.*, 2021), while surpassing it in the Technology and Management areas that are of interest to this study (Gavel & Iselid, 2008). We thus believe our findings to be valid while still benefitting from cross-validation with another database (e.g., EBSCO Business Source Premiere). Secondly, the formulation of critical factors for success or failure can be criticised as being subjective. However, we believe through rigorously applying the principles outlined by Elo & Kyngäs (2008), as well as having each step of the analysis conducted by at least two researchers (Snyder, 2019), to have limited that risk as much as possible. Third, our analysis did not differentiate by contextual factors, for example by industry, value network or business model maturity. As pointed out in the previous section, the impact of critical factors might differ by context. However, we still believe our analysis to be valid on a high level, as the common denominator of all value networks is the impact of digitalisation and dematerialisation on business practices (Ricciotti, 2020).

Despite these limitations, we believe our study significantly contributes to theory and practice. From a theoretical perspective, it closes a research gap by identifying critical factors contributing to success or failure of business models in value networks. This meets the demand of Jocevski *et al.* (2020) calling for studies that go beyond empirical examples and case studies to deepen our understanding of networked business models. The list of critical factors and the corresponding literature provides an extensive knowledge base that can help researchers target their activities to contribute to the further theorisation of business models in value networks. For practitioners, the factors and dimensions identified can serve as target variables when designing value networks or to guide business practices in existing value networks to ensure their success. This meets the demand of Ricciotti (2020), calling for levers that managers can utilise to ensure a sustainable competitive advantage of their value network.

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Technology Transformation, Innovation, and Digital Economy Development in Developing Countries

A Systematic Literature Review

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Abstract: The COVID-19 pandemic is a gateway for businesses to develop technology and embrace digitalization to remain competitive. Various results stated the important role of innovation and technology transformation as potent weapons for survival in this evolving landscape. This research analyzes the role of technology and innovation, especially in developing countries, with few articles researching this field. A systematic literature review that examined 84 articles from reputable international journals was used, with a particular emphasis on developing countries. This research aimed to conduct a comprehensive analysis of existing literature by using the keywords "technology", "innovation", and "digital economy" to identify gaps and generate fresh insights. The articles were collected from ProQuest, Google Scholar, and Scopus search engines and imported into Mendeley software for analysis using VOSviewer. The visualization results showed that SMEs were the most frequently mentioned keyword with 41 occurrences. This research contributed by providing opportunities in the form of new paths and variables rarely used for further analysis. There were also implications for organizational management, both in profit and non-profit organizations, to enhance technological capabilities, thereby improving business efficiency and sustainability.

Keywords: Digital Economy, Innovation, Technology, VOSviewer

Introduction

The COVID-19 pandemic is having negative impacts across various sectors, including society, the economy, education, healthcare, and the way of life of the global community (Akkad & Mouselli, 2023; Al-Mannaei *et al.*, 2023; Bouzakhem *et al.*, 2023; Carlos *et al.*, 2022; Uleanya, 2023; Grigorescu *et al.*, 2023; Nan & Park, 2022). Several research papers have reported technology implementation in business development as a solution to environmental uncertainty and intense competition in profit-oriented organizations, government, and the education sector (Almatrodi & Skoumpopoulou, 2023; Amoah *et al.*, 2023; Chemma, 2021; Shao *et al.*, 2022; Ssemugenyi & Nuru Seje, 2021). This implementation is also a primary strategy for many companies when facing pandemic, serving as a tool to formulate strategies for navigating turbulence and fulfilling consumer preferences (Alawamleh *et al.*, 2023; Almunawar & Anshari, 2022; Lontchi *et al.*, 2023; Pasciaroni *et al.*, 2022; Rodchenko *et al.*, 2021). Furthermore, it expedites communication with stakeholders, streamlines asset management, reduces costs, and increases revenue (Othman *et al.*, 2023; Pierre *et al.*, 2022; Polas *et al.*, 2022). From an employee perspective, digital implementation in Small and Medium Enterprises (SMEs) increases motivation when the technology is beneficial and user-friendly, resulting in improved performance (Uzkurt *et al.*, 2023). Therefore, a company strives to respond and adapt to changes in business plans to stay in line with the evolving times and goals (Faasolo & Sumarliah, 2022). The technology implementation will facilitate organizations to adopt strategies, including innovation to enhance productivity and meet market demands (Pea-Assounga & Yao, 2021).

The innovation process also serves as a driver for the advancement of manufacturing and construction companies toward a digital economy, capable of reducing disparities as well as enhancing productivity and international competitiveness (Guang-lin & Tao, 2022; Shkabatur *et al.*, 2022; Stojanovska-Georgievska *et al.*, 2022). The concept is a fundamental force that facilitates the production transformation processes and economic systems within a country (Carvache-Franco *et al.*, 2022; Casadella & Tahi, 2021; Mahmutaj *et al.*, 2021). In addition, innovation plays a crucial role during and after the COVID-19 pandemic, because the infection poses challenges to creating new business models and creative ideas in line with market needs and customer expectations (Bouzakhem *et al.*, 2023; Nguyen *et al.*, 2022; Valdez-Juárez *et al.*, 2022). Open innovation becomes increasingly relevant in disseminating information to address digital disparities in a region. Even though traditional businesses rely on internal resources, this concept leans on openness to welcome ideas from external experts (Kurmanov *et al.*, 2022; Osorno-Hinojosa *et al.*, 2022), enhancing company performance (Valdez-Juárez *et al.*, 2022).

Therefore, this research identifies gaps and opportunities for future analyses related to technology implementation, innovation, and the digital economy in developing countries to answer the following questions:

1. How can research on technology, innovation, and digital economy be clustered?
2. What are the most published research trends?

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3. What topics provide opportunities for future research?

Technology and innovation remain key factors in addressing competition and environmental changes in SMEs. Many previous research studies explored the concept of innovation with various supporting variables, such as Internet banking (Pea-Assounga & Yao, 2021); knowledge diffusion (Al-Mannaei *et al.*, 2023); company size (Carvache-Franco *et al.*, 2022) and e-commerce (Valdez-Juárez *et al.*, 2022), which enhances performance (Ureña-Espaillat *et al.*, 2022). Several research papers attempt to connect technology implementation with employee competence, financial resources (Amoah *et al.*, 2023) project success (Kamdjoug, 2023) or entrepreneurial orientation (Al-Hakimi *et al.*, 2021). Furthermore, none of the research has used digital economy as a variable. The development of digital economy is a condition where organizations or governments begin to shift their strategies to digital technology to improve efficiency (Guang-lin & Tao, 2022). This research will summarize a literature review to identify new novelties.

The development of technology, innovation, and the digital economy in developing countries was analyzed because: 1) the ability to exploit technology was significantly different from developed countries (Pea-Assounga & Yao, 2021); 2) the COVID-19 pandemic prompted small businesses in developing countries to use technology and innovate significantly (Lontchi *et al.*, 2023); 3) developing countries faced barriers in the innovation process due to limited resources and information, and an inability to bear the risk of failure (Carvache-Franco *et al.*, 2022; Hart *et al.*, 2022; Kamdjoug, 2023); 4) the literature development in this field is slow, due to low technology adoption rates (Amoah *et al.*, 2023); 5) many variables did not have a significant impact on technology implementation, such as risk-taking (Polas *et al.*, 2022), complexity and relative advantage (Amoah *et al.*, 2023), compatibility (Alshaher *et al.*, 2023), and competitive pressure (Justino *et al.*, 2022; Nguyen *et al.*, 2022).

Related Works

This research is carried out by reviewing various results, specifically in developing countries, facing different resource limitations in technology implementation (Amoah *et al.*, 2023). In this section, the results from various developing countries will be analyzed based on keywords to obtain a general overview of opportunities for further research.

Technology transformation

Technology transformation and organizational capacity pose serious challenges in many developing countries (Almatrodi & Skoumpopoulou, 2023; Oubrahim *et al.*, 2023). Furthermore, e-commerce and artificial intelligence have altered the behaviour of entrepreneurs in India, SMEs in Libya (Chatterjee *et al.*, 2021; Omar & Elmansori, 2021), as well as the perspectives of the public sector in Tanzania and traditional companies in Azerbaijan, compelling companies to innovate in marketing, specifically during the pandemic (Shao *et al.*, 2022). The concept offers new hope for SMEs in Mexico to compete both locally and globally (Valdez-Juárez *et al.*, 2022), enhances efficiency, addresses environmental uncertainty, increases competitiveness, and ensures the survival of several SMEs in Russia, Serbia, El Salvador, and Uzbekistan (Akberdina *et al.*, 2023; Cvijić Čović *et al.*, 2023; Flores-Hernández *et al.*, 2022; Tuychiev, 2022), and performance in Tunisia (Bellakhal & Mouelhi, 2023). Meanwhile, financial technology, as part of technological advancement, has greatly assisted new entrepreneurs in Cameroon and Zambia in entering the market due to its flexibility and efficiency (Lontchi *et al.*, 2023; Nan & Park, 2022). The concept also provides many benefits for assessing risk in financial companies in South Sudan (Kshetri, 2021).

In the current era of globalization, retail companies in Thailand and SMEs in Ghana are increasingly adopting modern technology to significantly increase business growth. Social media is one form of technology used to bridge the gap between businesses and consumers in Angola and banking customers in Zimbabwe (Amoah *et al.*, 2023; Justino *et al.*, 2022; Kaondera *et al.*, 2023; Nguyen *et al.*, 2022). Moreover, the digital transformation conducted in Pakistan and Rwanda provides new directions and pathways for further digital innovation, enhances the competitiveness and sustainability of SMEs in Indonesia (Budiarto *et al.*, 2023; Naicker & Nsengimana, 2023; Sarfraz *et al.*, 2022), and improves the digital agriculture value chain of South Africa (Smidt & Jokonya, 2022). In Tonga, sustainability is influenced by the attitude within a company, and this is affected by external factors (Faasolo & Sumarliah, 2022). As a developing country, rapid technological changes pose a challenge in the Democratic Republic of Congo. Therefore, a change in management with a focus on improving human resources is the best solution (Kamdjoug, 2023). Different results are shown in Oman, where technology transformation, digitalisation and the use of e-commerce influence SMEs' operational efficiency on performance. The performance of a company is better when SMEs use technology, specifically when facing the COVID-19 pandemic (Mishrif & Khan, 2022).

Several results use the term "technology", as exemplified by research in the Democratic Republic of Congo conducted by Kamdjoug (2023). This research adopted a quantitative method with 229 managers from SMEs to examine the impact of management changes and IT strategy on project success and company performance. The results showed that project objective, team expertise, and IT strategy impact project success. Meanwhile, three other variables, namely communication, management support, and stakeholder acceptance, did not affect project success. The results from this research in the Democratic Republic of Congo were intriguing because most SMEs were less than 5 years old, making the digital transformation

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process challenging. To achieve success, SMEs need high-quality resources and the ability to translate the company strategy and objectives.

Innovation

Innovation is a company tendency to discover new ideas that lead to the development of new products or services to enhance customer satisfaction. The development of new technology poses challenges for businesses in Trinidad and Tobago and Uganda (Eton *et al.*, 2021; Mohan *et al.*, 2021), as well as for small businesses due to limited resources. However, it is the best solution as a powerful weapon to compete in the market (Chemma, 2021). Research conducted in Kuwait, Mauritius, and Somalia stated that collaboration between academia, the company and the government was crucial for developing innovation as a future challenge (Daka & Siad, 2021). Academics design programs for a company, while the government provides effective policies and a conducive business environment (Arman & Al-Qudsi, 2022; Roopchund, 2023). These results are supported by research in Malaysia and Moldova, where digital capability and government support enhance SMEs' innovation and competitiveness (Larisa *et al.*, 2022; Teoh *et al.*, 2023). Results in Argentina explained that innovation is key for the hotel sector to survive during the COVID-19 pandemic (Pasciaroni *et al.*, 2022) and improve the performance of textile companies in Pakistan and Liberia, as well as SMEs in the Republic of Congo, Ecuador and Kosovo (Mahmutaj *et al.*, 2021; Sarfraz *et al.*, 2022; Sumo *et al.*, 2022).

The research conducted in Madagascar, Bahrain, and the Philippines showed that innovation is crucial for companies. Therefore, managers must create an environment where new knowledge is continually developed, and infrastructure is available to facilitate the development of new ideas (Al-Mannaei *et al.*, 2023; Bayudan-Dacuycuy & Dacuycuy, 2022; Hart *et al.*, 2022). SMEs should compete vigorously to survive in Bangladesh, due to the rapidly changing environment (Polas *et al.*, 2022). Results in Brazil, Bolivia, Chile and Nigeria explained that limited resources hindered innovation (Shamaki *et al.*, 2022; Vila, 2022; Zapata & Orellana, 2022). Consequently, government support is needed to enable the production of new products, processes and innovative marketing methods, enhancing productivity and creating jobs (Castella *et al.*, 2022; Shkabatur *et al.*, 2022). Lack of knowledge, financial resources, and market information have driven many companies in Ecuador and Nepal to innovate significantly (Carvache-Franco *et al.*, 2022; Rajbhandari *et al.*, 2022).

Based on the keyword "innovation" used in several previous studies, various diverse conclusions have been drawn: for example, the results in Ecuador on 6,275 companies in various sectors using a quantitative method (Carvache-Franco *et al.*, 2022). The research aimed to analyze 10 factors that potentially hinder companies from innovating in process and

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product. The results indicate that there are between 6 and 8 factors hindering product and process innovation. The research is interesting because demand uncertainty does not affect innovation, meaning that company strategies still focus on internal factors, such as finances and knowledge. Meanwhile, external factors, such as market barriers, are not the main target for companies.

Digital economy

Digital economy is a concept that integrates production methods with information technology, including digital platforms. Therefore, it requires technology (digital technology and digital innovation) to break the constraints of space and time, accelerating business processes in companies (Błaszczyk *et al.*, 2023; Guang-lin & Tao, 2022). Companies are making extensive use of technology because the concept can transform business strategies and processes, products and services, and the capabilities of the digital economy environment (Błaszczyk *et al.*, 2023; Pierre *et al.*, 2022). Compared to traditional management, a digital economy can stimulate company growth, expand markets, enhance competitiveness, and change economic structure (Rodchenko *et al.*, 2021). As an integration of information technology, the concept offers new strategic options for company transformation in China. This is because the digital economy can break spatial and temporal limitations, contributing to growth (Guang-lin & Tao, 2022). Furthermore, the development of technology integrated with business operations in Morocco and Iran facilitates the flow of supply chain information, reducing waste, improving flexibility, and speeding up decision-making (Khodaparasti & Garabollagh, 2023; Oubrahim *et al.*, 2023).

Several new startups (98% SMEs) in Jordan have made significant use of technology and are considered agents of change, because they effectively generate new products and services, absorb labour, and stimulate digital economy growth (Alawamleh *et al.*, 2023). Technology advancement, such as cloud technology, will continue to accelerate, because it is easily accessible from anywhere. Therefore, its role in the development of the digital economy in Kazakhstan, Thailand and Iraq is highly significant (Alshaher *et al.*, 2023; Kurmanov *et al.*, 2022; Sastararuji *et al.*, 2022). In line with several examinations in Romania for education institutions, Sri Lanka for SMEs, and Cambodia for the government prove that human resource capabilities and technology expedite the transformation process towards a digital economy (Grigorescu *et al.*, 2023; Savuth & Sothea, 2023; Thathsarani & Jianguo, 2022).

The results related to digital economy research show that the concept is very important for development. Therefore, the government should intervene in the form of policies in this direction (Grigorescu *et al.*, 2023; Thathsarani & Jianguo, 2022). Based on the results of various previous analyses, there are no articles that specifically use digital economy as a variable to be tested. However, the importance of the concept was explained to support progress in developing countries.

Data and Methodology

This research uses a qualitative method with a Systematic Literature Review (SLR) to find answers to the three questions mentioned in the previous section. In the pre-analysis, only one article that used the SLR method focused on agriculture in South Africa (Smidt & Jokonya, 2022). The keywords are 'digital development', 'Small-scale farmer', 'Agriculture value chains', 'framework', 'institution', and 'innovation'. This research was divided into five stages: 1) formulating the problem; 2) collecting data and literature; 3) evaluating the quality of articles; 4) conducting analysis; 5) presenting and interpreting the results of the analysis. The same steps were followed, starting with problem formulation in the introduction section, and then gathering articles using keywords, presented in the method.

Step 1: This research was conducted by using the keywords 'technology', 'innovation' and 'digital economy', followed by the inclusion of the names of developing countries. According to the IMF (International Monetary Fund), there were 152 developing countries worldwide, resulting in 152 times searches using the ProQuest search engine. This research was restricted to scholarly journals indexed in Scopus with the document type being articles within the timeframe of 2021–2023 during the COVID-19 pandemic. Based on the ProQuest search engine, 39 articles from 39 countries were found, but 4 were not indexed in Scopus, leaving 35 usable.

Step 2 included searching for the remaining 117 countries on Google Scholar and Scopus with 117 times searches, yielding 49 articles from 49 developing countries. The total number of articles obtained from ProQuest and Scopus search engines was 84 from 84 developing countries. In cases where multiple articles pertained to the same subject (the same countries), one was selected based on the criteria of the latest year, the highest quartile, and the most keywords. Several results were not used as subjects of analysis since more than one country was discussed. The final step included processing the 84 articles in the Mendeley software and then exporting the data into an RIS file.

The analysis using VOSviewer only considered keywords that appear a minimum of two times or are used in at least two papers. The total number of keywords based on the analysis is 292, which VOSviewer then categorizes into 33 items, as shown in Table 4. The final result of the analysis includes the number of clusters and a visualization of the results, showing the relationships between keywords or variables used. The results showed that there were 60% SMEs and 40% non-SMEs (industries, government institutions, education institutions) among the types of businesses. For the method used, 64% were quantitative, while 36% were

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qualitative (Table 1). Table 2 provides categorization based on journal publication year and quartiles according to Scopus.

Table 1. Analysis results using Crosstab

Types	Quantitative	Qualitative
SMEs	35	16
Non-SMEs	17	16
Total	**52**	**32**

Table 2. Journal quartiles by year

Quartile	2021	2022	2023
<25%	-	3	2
25-50%	3	6	2
50-75%	7	12	11
>75%	3	22	13
Total	**13**	**43**	**28**

Results & Discussion

Figure 1 is the result of clustering using VOSviewer to answer research question number 1, namely clustering research on technology, innovation, and digital economy. The results show that there are 8 clusters (the size of the dot in the Figure is directly proportional to the number of keywords used). The main keywords of clusters 1, 2, 3, 4, 5, 6, 7, and 8, with red, green, blue, yellow, purple, light blue, orange, and brown colours are ‘digital transformation’, ‘SMEs’, ‘circular economy’, ‘Covid-19,’ ‘developing countries’, ‘open innovation’, ‘innovation’, and ‘technology’, respectively.

This systematic literature review examined 84 articles discussing technology transformation and innovation in developing countries using two occurrences to obtain 33 related keywords. The frequency of keywords and link strength (Table 4) served as an entry point for future research opportunities.

The second research question about publication trends can be answered in Tables 3 and 4. In Table 4, the most used keywords are ‘SMEs’ (Cluster 2), while Table 3 shows Cluster 2 with keywords ‘SMEs’, ‘SEM’, ‘Artificial intelligence’, ‘TAM’, ‘Financial inclusion’, ‘E-commerce’, and ‘Entrepreneurial orientation’. In Cluster 2, the number of occurrences for ‘SMEs’ is 41 with a total link strength of 76, indicating that this theme has been extensively studied by previous research. In Cluster 1, the number of occurrences for ‘Human capital’ is 2 with a total link strength of 4, meaning there is an opportunity for further exploration of the human capital variable discussed in the clustering discussion.

The third question about topics is analyzed based on each cluster, serving as an opportunity for future research. To obtain new ideas, each cluster (Clusters 1-8) will be linked to others as follows.

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Cluster 1: In Cluster 1, *digital transformation* is the most frequently used keyword with 11 occurrences and a link strength of 12. The results indicate that management capability enhances the digital transformation process and has an impact on technology innovation (Guang-lin & Tao, 2022), including bank customer management (Kaondera *et al.*, 2023), leading to improved performance and sustainability (Budiarto *et al.*, 2023; Sarfraz *et al.*, 2022). Human capital has an impact on digital transformation (Rodchenko *et al.*, 2021), enhancing supply chain performance (Oubrahim *et al.*, 2023). These results have potential connections to Cluster 4 (Bouzakhem *et al.*, 2023), artificial intelligence, and acceptance model theories in Cluster 2 (Chatterjee *et al.*, 2021; Polas *et al.*, 2022). Furthermore, the relationship between digital transformation and innovation can be tested with the role of the government, as shown in Cluster 2 (Rajbhandari *et al.*, 2022). The description of some previous results can be explained by creating a new model that combines several previous research variables. Innovation variables are used as the first step by finding supporting factors, such as management ability and digital transformation (Guang-lin & Tao, 2022), as well as government intention (Rajbhandari *et al.*, 2022). Furthermore, it is a challenge for future research to determine theories connecting digital transformation with government intervention to build a mediating relationship.

Cluster 2: In Cluster 2, 'SMEs' is the keyword with the highest occurrence, namely 41, and a link strength of 76. In this cluster, some research emphasizes the importance of financial inclusion, digital finance, and technology adoption in enhancing the growth and performance of SMEs (Eton *et al.*, 2021; Thathsarani & Jianguo, 2022). Other results explain the implementation of technology digitalization in increasing employee motivation and performance (Uzkurt *et al.*, 2023). In Cluster 1, digitalization can strengthen the impact of innovation on organizational performance (Sarfraz *et al.*, 2022). Additionally, the research by Polas *et al.* (2022), Rajbhandari *et al.* (2022) and Sharma *et al.* (2022) on knowledge of artificial intelligence related to technology adoption, with the role of the government as mediation, can be linked to entrepreneurship and digitalization in Cluster 5 (Akulava & Guerrero, 2022; Shkabatur *et al.*, 2022) and Cluster 1 (Pierre *et al.*, 2022). Building a new model in this cluster can be started with the impact between technology and SMEs performance (Thathsarani & Jianguo, 2022) as well as innovation (Sarfraz *et al.*, 2022). The new model developed is to test the mediation impact between technology implementation and innovation on performance.

Cluster 3: Cluster 3 consists of 4 keywords, namely *circular economy, competitive advantage, business strategy,* and *sustainability,* each with two occurrences. Results in this cluster show (Amoah *et al.*, 2023) that technology influences social media implementation and enhances sustainability in SMEs. Additionally, sustainability is an outcome of circular economy practices (Khodaparasti & Garabollagh, 2023). Different results indicate that external factors affect internal factors, enhancing sustainability (Faasolo & Sumarliah, 2022). For example, Valdez-Juárez *et al.* (2022) stated that e-commerce, business strategy and innovation improved the performance of SMEs. In Cluster 2, the application of technology is influenced by artificial intelligence knowledge (Polas *et al.*, 2022). Various results above can be related to the keyword *competitiveness* in Cluster 7 (Teoh *et al.*, 2023; Tuychiev, 2022).

The overview of the results can be explained by using a model that explains the impact of business strategy and e-commerce on performance (Valdez-Juárez *et al.*, 2022). The opportunity carried out is to build a new model by connecting e-commerce, performance and sustainability using research developed by Amoah *et al.* (2023).

Cluster 4: In Cluster 4, COVID-19 is the most frequently used keyword with 12 occurrences and a link strength of 20. In this cluster, Bouzakhem *et al.* (2023) explained different factors impacting the performance of SMEs' employees. Furthermore, employee performance is related to Cluster 8, by the improvement of SMEs' performance (Lontchi *et al.*, 2023; Pea-Assounga & Yao, 2021). Another research paper using a case study method found various factors affecting knowledge sharing, such as human resources, processes and organisational culture (Carlos *et al.*, 2022). However, the variable only has an impact on innovation when the company is in a low manufacturing technology environment (Bianchi & Machado, 2021). This research is further developed by conducting a more in-depth analysis based on strategy and company type, as in Cluster 6 (Pilav-Velic & Hatidza, 2021).

A more in-depth explanation of this cluster can be started by examining the factors impacting employee performance, namely resilience and empowerment (Bouzakhem *et al.*, 2023). Meanwhile, others examine the impact of Internet banking and innovativeness on employee performance (Pea-Assounga & Yao, 2021). Future research interested in this theme can establish a mediating relationship between Internet banking, empowerment and performance by using relevant theories.

Cluster 5: In Cluster 5, the keyword *developing countries* has 7 occurrences with a link strength of 16. This result (Pierre *et al.*, 2022) proves that, in developing countries, the role of digital technology is significant in improving the capabilities toward better performance. Meanwhile, other research in Cluster 1 stated that innovation bridges the relationship between technology and performance (Sarfraz *et al.*, 2022). In Cluster 3, business strategy also has a significant effect on innovation (Valdez-Juárez *et al.*, 2022). Some of the results can also be connected to Cluster 2, where women business owners in SMEs face limitations in entrepreneurship due to resource constraints, socio-cultural factors, knowledge and skills (Lim *et al.*, 2022).

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Table 3. Number of authors based on cluster

Clusters	Keywords	Authors
Cluster 1	Digital transformation; Digitalization; Digital economy; Digital capability; Business; Human capital; Internationalization	Almatrodi & Skoumpopoulou, 2023; Alshaher *et al.*, 2023; Bayudan-Dacuycuy & Dacuycuy, 2022; Bellakhal & Mouelhi, 2023; Błaszczyk *et al.*, 2023; Budiarto *et al.*, 2023; Chatterjee *et al.*, 2021; Cvijić Čović *et al.*, 2023; Grigorescu *et al.*, 2023; Guang-lin & Tao, 2022; Hart *et al.*, 2022; Kaondera *et al.*, 2023; Kurmanov *et al.*, 2022; Naicker & Nsengimana, 2023; Othman *et al.*, 2023; Oubrahim *et al.*, 2023; Pierre *et al.*, 2022; Rodchenko *et al.*, 2021; Sarfraz *et al.*, 2022; Savuth & Sothea, 2023; Shao *et al.*, 2022; Stojanovska-Georgievska *et al.*, 2022; Valiyev *et al.*, 2022
Cluster 2	SMEs; SEM; Artificial intelligence; TAM; Financial inclusion; E-commerce; Entrepreneurial orientation	Akkad & Mouselli, 2023; Al-Hakimi *et al.*, 2021; Alshaher *et al.*, 2023; Bellakhal & Mouelhi, 2023; Budiarto *et al.*, 2023; Chatterjee *et al.*, 2021; Cvijić Čović *et al.*, 2023; Eton *et al.*, 2021; Faasolo & Sumarliah, 2022; Flores-Hernández *et al.*, 2022; Gansonré & Ouédraogo, 2022; Justino *et al.*, 2022; Kamdjoug, 2023; Kshetri, 2021; Larisa *et al.*, 2022; Lim *et al.*, 2022; Mahmutaj *et al.*, 2021; Akulava & Guerrero, 2022; Mishrif & Khan, 2022; Naicker & Nsengimana, 2023; Nan & Park, 2022; Nguyen *et al.*, 2022; Omar & Elmansori, 2021; Polas *et al.*, 2022; Rajbhandari *et al.*, 2022; Rodchenko *et al.*, 2021; Sastararuji *et al.*, 2022; Sharma *et al.*, 2022; Smidt & Jokonya, 2022; Teoh *et al.*, 2023; Thathsarani & Jianguo, 2022; Uzkurt *et al.*, 2023; Valdez-Juárez *et al.*, 2022; Vila, 2022; Zapata & Orellana, 2022
Cluster 3	Circular economy; Competitive advantage; Business strategy; Sustainability	Akberdina *et al.*, 2023; Amoah *et al.*, 2023; Budiarto *et al.*, 2023; Faasolo & Sumarliah, 2022; Khodaparasti & Garabollagh, 2023; Sumo *et al.*, 2022; Ureña-Espaillat *et al.*, 2022; Valdez-Juárez *et al.*, 2022
Cluster 4	COVID-19; Challenges; Knowledge sharing	Akkad & Mouselli, 2023; Almunawar & Anshari, 2022; Bianchi & Machado, 2021; Bouzakhem *et al.*, 2023; Carlos *et al.*, 2022; Grigorescu *et al.*, 2023; Mishrif & Khan, 2022; Naicker & Nsengimana, 2023; Nan & Park, 2022; Sastararuji *et al.*, 2022; Shao *et al.*, 2022; Teoh *et al.*, 2023
Cluster 5	Developing countries; Entrepreneurship; Economy growth	Alawamleh *et al.*, 2023; Chatterjee *et al.*, 2021; Daka & Siad, 2021; Gansonré & Ouédraogo, 2022; Kshetri, 2021; Akulava & Guerrero, 2022; Mohan *et al.*, 2021; Pierre *et al.*, 2022; Roopchund, 2023; Shkabatur *et al.*, 2022; Zapata & Orellana, 2022
Cluster 6	Open innovation; Hotel; Knowledge management	Kurmanov *et al.*, 2022; Metawa *et al.*, 2021; Osorno-Hinojosa *et al.*, 2022; Pasciaroni *et al.*, 2022; Pilav-Velic & Hatidza, 2021
Cluster 7	Innovation; Competitiveness; Economy development	Al-Hakimi *et al.*, 2021; Al-Mannaei *et al.*, 2023; Arman & Al-Qudsi, 2022; Bianchi & Machado, 2021; Carvache-Franco *et al.*, 2022; Casadella & Tahi, 2021; Castella *et al.*, 2022; Chemma, 2021; Daka & Siad, 2021; Larisa *et al.*, 2022; Mahmutaj *et al.*, 2021; Akulava & Guerrero, 2022; Mohan *et al.*, 2021; Rajbhandari *et al.*, 2022; Shkabatur *et al.*, 2022; Sinatoko Djibo *et al.*, 2022; Sumo *et al.*, 2022; Teoh *et al.*, 2023; Tuychiev, 2022; Ureña-Espaillat *et al.*, 2022; Valiyev *et al.*, 2022; Vila, 2022
Cluster 8	Technology; Fintech; Performance	Ahmed *et al.*, 2022; Bellakhal & Mouelhi, 2023; Dumenu *et al.*, 2023; Justino *et al.*, 2022; Lontchi *et al.*, 2023; Mishrif & Khan, 2022; Mohan *et al.*, 2021; Nguyen *et al.*, 2022; Pea-Assounga & Yao, 2021; Polas *et al.*, 2022; Thathsarani & Jianguo, 2022; Tuychiev, 2022; Ureña-Espaillat *et al.*, 2022

The overview of previous research in Cluster 5 can be explained with a research model that examines the impact of technology implementation using the moderating variable of the creative industry (Pierre *et al.*, 2022). Meanwhile, other research explains the relationship between innovation and company performance (Sarfraz *et al.*, 2022; Valdez-Juárez *et al.*, 2022). The results of the three research papers can be developed into a new model by testing the moderating impact of the creative industry using relevant theories.

Cluster 6: In Cluster 6, there are 3 keywords, namely *open innovation, hotel,* and *knowledge management,* but *open innovation* has the most occurrences and link strength. Therefore, the implementation of open innovation depends on the strategy used, company type, and collaboration with external partners (Pilav-Velic & Hatidza, 2021). Open innovation supported by human capital can create additional opportunities for acquiring new knowledge and ideas bridging digital gaps (Kurmanov *et al.*, 2022). Other research examined the innovation process in hotels, showing that the COVID-19 pandemic was not a trigger for innovation but an inhibition (Pasciaroni *et al.*, 2022). Some of these results connect entrepreneurship and knowledge sharing in Cluster 5 (Akulava & Guerrero, 2022) and Cluster 4 (Carlos *et al.*, 2022). A more detailed explanation of this cluster's potential is combining the strategy impact model on innovation (Pilav-Velic & Hatidza, 2021) with gender (Akulava & Guerrero, 2022).

Cluster 7: Based on the visualization in Cluster 7, the keyword *innovation* appears with a total of 33 links, connected to keywords such as *competitiveness* and *fintech*. Results in this cluster include research on innovation in both large and small companies by Al-Mannaei *et al.* (2023) and Carvache-Franco *et al.* (2022). Other results regarding eco-innovation prove that government support enhances innovation capability, but market performance weakens the relationship (Sinatoko Djibo *et al.*, 2022). In line with research in Malaysia, innovation is influenced by digital capability, government support, entrepreneurial orientation, and entrepreneurial leadership, supporting competitiveness and supply chain resilience (Al-Hakimi *et al.*, 2021; Teoh *et al.*, 2023). Results in this cluster can be further developed by connecting with other keywords in Cluster 3, such as *sustainability* (Amoah *et al.*, 2023), *business strategy* (Valdez-Juárez *et al.*, 2022), and *competitive advantage* (Budiarto *et al.*, 2023). Based on the results of previous research with quantitative methods, a new model can be presented by combining factors that impact innovation, such as knowledge (Al-Mannaei *et al.*, 2023), entrepreneurial orientation (Al-Hakimi *et al.*, 2021), and lack of information technology (Carvache-Franco *et al.*, 2022), further connecting the concept with competitive advantage (Teoh *et al.*, 2023) or sustainability (Budiarto *et al.*, 2023).

Cluster 8: In Cluster 8, there are keywords such as technology, fintech and performance, but technology has 16 occurrences with a link strength of 31. In this cluster, previous results (Lontchi *et al.*, 2023) provided evidence that using fintech could directly enhance SMEs' performance through financial literacy. Furthermore, the implementation of technology, organizational factors, and the environment improve digital transformation toward better performance (Justino *et al.*, 2022; Nguyen *et al.*, 2022). Additional results also explain that digitalisation can increase sales and growth for SMEs (Bellakhal & Mouelhi, 2023). These present opportunities for future research when connected to Cluster 7, which focuses on innovation (Al-Mannaei *et al.*, 2023). The impact of technology and e-commerce on the relationship between the operations and performance of a company is also stated (Mishrif & Khan, 2022). This result offers opportunities for further development by incorporating keywords such as 'competitive advantage' and 'sustainability' in Cluster 3 (Budiarto *et al.*, 2023). The explanation of the opportunities is to start from the various antecedent factors impacting the use of m-commerce in SMEs (Justino *et al.*, 2022). This can be connected to competitive advantage and sustainability to obtain a new research model (Budiarto *et al.*, 2023).

Table 4. Number of occurrences and link strength

Clusters	Keywords	Occurrence	Total Link Strength
Cluster 1	Digital transformation	11	12
	Digitalization	6	12
	Digital economy	4	8
	Digital capability	2	5
	Business	2	4
	Human capital	2	4
	Internationalization	2	4
Cluster 2	SMEs	41	76
	SEM	6	12
	Artificial intelligent	3	7
	TAM	3	5
	Financial inclusion	3	5
	e-commerce	2	6
	Entrepreneurial orientation	2	4
Cluster 3	Circular economy	2	6
	Competitive advantage	2	6
	Business strategy	2	5
	Sustainability	2	5
Cluster 4	COVID-19	12	20
	Challenges	2	3
	Knowledge sharing	2	2
Cluster 5	Developing countries	7	16
	Entrepreneurship	6	12
	Economy growth	2	3
Cluster 6	Open innovation	5	7
	Hotel	2	4
	Knowledge management	2	4
Cluster 7	Innovation	21	33
	Competitiveness	2	5
	Economy development	2	1
Cluster 8	Technology	16	31
	Fintech	2	5
	Performance	2	4

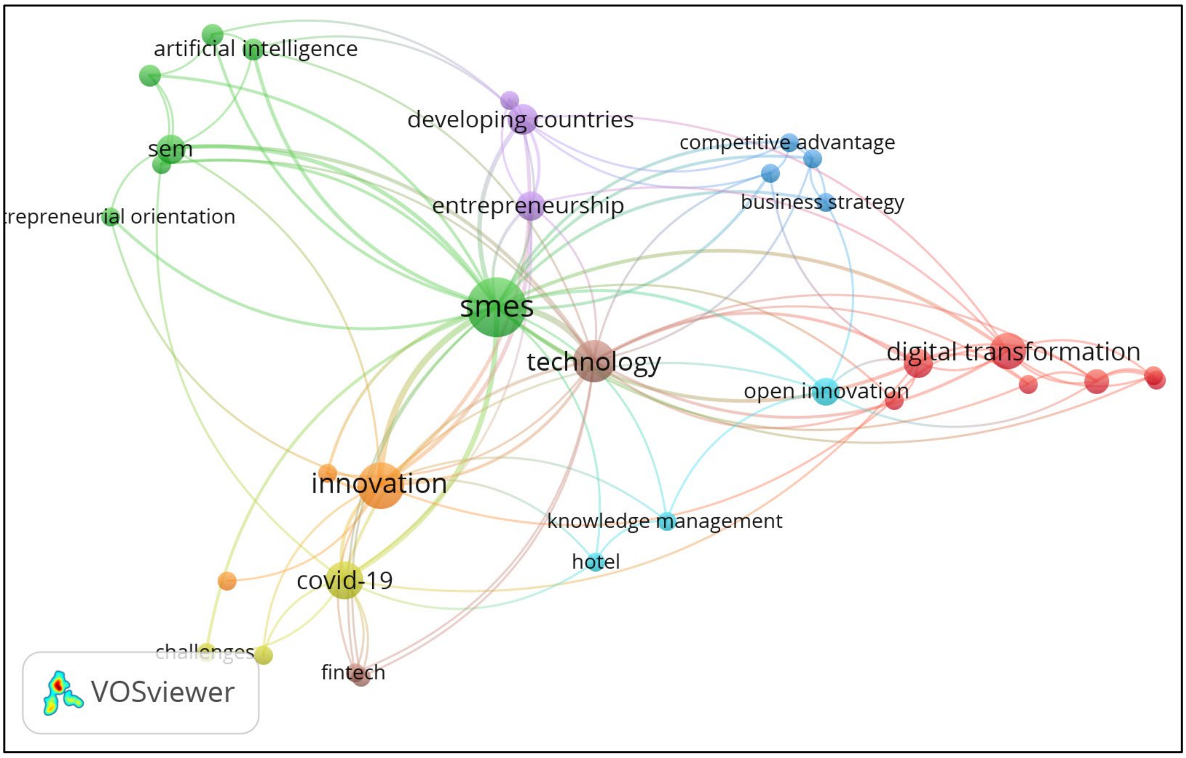

Figure 1. Analysis results with VOSviewer

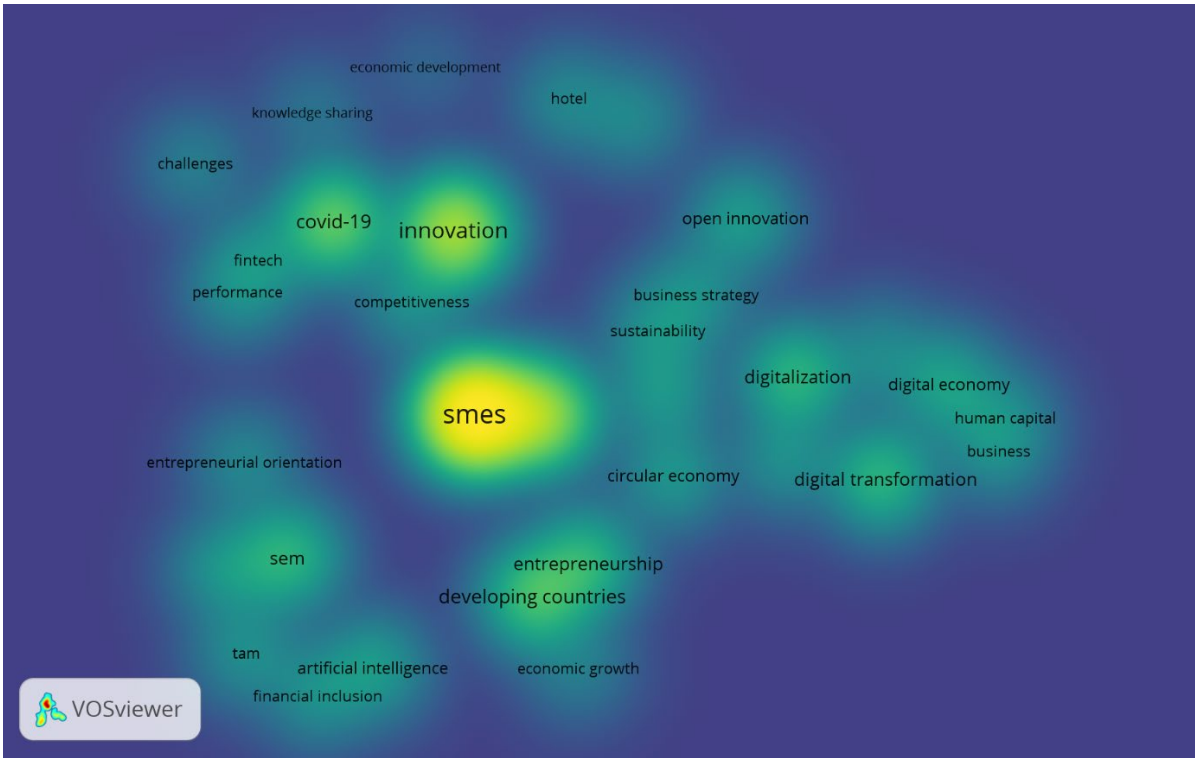

Figure 2. Density display result

Conclusions/Recommendations

In conclusion, the visualization results using VOSviewer were indicative of the variable 'SMEs' as the most frequently observed keyword across different articles. However, attention was drawn to Clusters 7 and 4, where the keywords 'economy development' and 'knowledge

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sharing' had only 1 and 2 link strengths. These keywords served as entry points for the fields of technology, innovation, and digital economy. Furthermore, it is essential for researchers that innovation, technology, and digital transformation variables have become trends nowadays, so finding novelty in this area will be a difficult challenge. Finally, based on the analysis results in Figure 2, many variables still have no connection, making it an opportunity for future research, especially in developing countries.

This research also presented several limitations to be considered for future analyses. First, there were no differences between subjects in low-income, lower, upper, or high-income countries, and future research could be tested based on income categories. This limitation was consistent with previous results that investing in infrastructure strengthened creativity and promoted innovation and technology adoption, which was a barrier for low-income countries (Al-Mannaei *et al.*, 2023; Bayudan-Dacuycuy & Dacuycuy, 2022).

Second, this research did not differentiate between the objects as small firms, large firms or government entities. This could be an opportunity for future research, because small businesses have limited resources for innovation (Dumenu *et al.*, 2023; Polas *et al.*, 2022; Thathsarani & Jianguo, 2022). Lastly, this research uses keywords with at least two occurrences, meaning keywords only used once did not appear in the analysis, such as 'e-government' (Shao *et al.*, 2022), 'start-up' (Alawamleh *et al.*, 2023) and 'digital education' (Grigorescu *et al.*, 2023).

Finally, this research only discussed the definition of digital economy, which according to practitioners is still ambiguous. Therefore, future analyses could show the definition of digital economy from various perspectives based on 5 levels of digital development (Kurmanov *et al.*, 2022).

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Appendix

No	Country	Author	Year of publication	Methodology	Study Period
1	Algeria	Chemma	2021	Qualitative	Sept 2013 - Jun 2016.
2	Angola	Justino *et al.*	2022	Quantitative	NA
3	Argentina	Pasciaroni *et al.*	2022	Qualitative	July - Oct 2020
4	Azerbaijan	Valiyev *et al.*	2022	Qualitative	Jan -May 2021
5	Bahrain	Al-Mannaei *et al.*	2023	Quantitative	Jan - Feb 2022
6	Bangladesh	Polas *et al.*,	2022	Quantitative	Feb - March 2022
7	Belarus	Akulava & Guerrero	2022	Quantitative	2017-2018
8	Benin	Sinatoko Djibo *et al.*	2022	Quantitative	Jul - Sept 2021
9	Bolivia	Vila	2022	Qualitative	2021
10	Bosnia	Pilav-Velic & Hatidza	2021	Quantitative	Oct. - Dec 2019
11	Brazil	Carlos *et al.*	2022	Qualitative	During Covid Pandemic
12	Botswana	Uleanya	2021	Qualitative	October 2021
13	Brunei	Almunawar & Anshari	2022	Quantitative	2021
14	Burkina Faso	Gansonré & Ouédraogo	2022	Quantitative	2014
15	Cambodia	Savuth & Sothea	2023	Qualitative	NA
16	Cameroon	Lontchi *et al.*	2023	Quantitative	During Covid Pandemic
17	Chile	Zapata & Orellana	2022	Qualitative	2021
18	China	Guang-lin & Tao	2022	Quantitative	2008-2029
19	D. Rep. of the Congo	Kamdjoug	2023	Quantitative	Jan - March 2021
20	Ecuador	Carvache-Franco *et al.*	2022	Quantitative	2015
21	Dominican	Ureña-Espaillat *et al.*	2022	Quantitative	2020
22	Egypt	Metawa *et al.*	2021	Qualitative	2019 - 2020
23	El Salvador	Flores-Hernández *et al.*	2022	Quantitative	2018
24	Eswatini	Ahmed *et al.*	2022	Qualitative	2018
25	Ethiopia	Shkabatur *et al.*	2022	Qualitative	NA
26	Fiji	Sharma *et al.*	2022	Quantitative	Nov - Dec 2020
27	Gambia	Lim *et al.*	2022	Qualitative	NA
28	Ghana	Amoah *et al.*	2023	Quantitative	June - Sept 2022
29	India	Chatterjee *et al.*	2021	Quantitative	Dec 2019 - Jan 2021
30	Indonesia	Budiarto *et al.*	2023	Quantitative	Sept - Dec 2022
31	Iran	Khodaparasti & Garabollagh	2023	Quantitative	April - July 2022
32	Iraq	Alshaher *et al.*	2023	Quantitative	Feb - Nov 2021
33	Jordan	Alawamleh *et al.*	2023	Qualitative	During Covid Pandemic
34	Kazakhstan	Kurmanov *et al.*	2022	Quantitative	2016 - 2021
35	Kosovo	Mahmutaj *et al.*	2021	Qualitative	2014-2016
36	Kuwait	Arman & Al-Qudsi	2022	Qualitative	2019 - 2021
37	Laos	Castella *et al.*	2022	Qualitative	2005-2020
38	Lebanon	Bouzakhem *et al.*	2023	Quantitative	Sept - Oct 2022
39	Liberia	Sumo *et al.*	2022	Qualitative	Nov 2021 - Feb 2022
40	Libya	Omar & Elmansori	2021	Quantitative	NA
41	Madagascar	Hart *et al.*	2022	Qualitative	March - April 2022
42	Malawi	Dumenu *et al.*	2023	Quantitative	June - August 2021
43	Malaysia	Teoh *et al.*	2023	Qualitative	Sept - Oct 2020
44	Mauritius	Roopchund	2023	Qualitative	NA
45	Mexico	Valdez-Juárez *et al.*	2022	Quantitative	Feb - Oct 2021
46	Moldova	Larisa *et al.*	2022	Quantitative	2015-2020
47	Morocco	Oubrahim *et al.*	2023	Quantitative	Aug - November 2022
48	Nepal	Rajbhandari *et al.*	2022	Quantitative	March - Dec 2020
49	Nicaragua	Osorno-Hinojosa *et al.*	2022	Qualitative	2018-2021
50	Nigeria	Shamaki *et al.*	2022	Quantitative	January 2021
51	North Macedonia	Stojanovska-Georgievska *et al.*	2022	Qualitative	2022
52	Oman	Mishrif & Khan	2022	Quantitative	During Covid Pandemic
53	Pakistan	Sarfraz *et al.*	2022	Quantitative	March - June 2022
54	Papua New Guinea	Ssemugenyi & Nuru Seje	2021	Quantitative	During Covid Pandemic
55	Peru	Pierre *et al.*	2022	Quantitative	2015
56	Philippines	Bayudan-Dacuycuy & Dacuycuy	2022	Quantitative	2019
57	Poland	Błaszczyk *et al.*	2023	Quantitative	2016 - 2021
58	Qatar	Othman *et al.*	2023	Qualitative	2019-2021
59	Rep of the Congo	Pea-Assounga & Yao	2021	Quantitative	Oct - Dec 2019
60	Romania	Grigorescu *et al.*	2023	Quantitative	2008-2021
61	Russia	Akberdina *et al.*	2023	Quantitative	June - Nov 2022
62	Rwanda	Naicker & Nsengimana	2023	Qualitative	During Covid Pandemic

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No	Country	Author	Year of publication	Methodology	Study Period
63	Saudi Arabia	Almatrodi & Skoumpopoulou	2023	Qualitative	May 2020
64	Senegal	Casadella & Tahi	2021	Qualitative	NA
65	Serbia	Cvijić Čović *et al.*	2023	Quantitative	Feb - April 2020
66	Somalia	Daka & Siad	2021	Qualitative	NA
67	South Africa	Smidt & Jokonya	2022	Qualitative	2021
68	South Sudan	Kshetri	2021	Qualitative	2019
69	Sri Lanka	Thathsarani & Jianguo	2022	Quantitative	Sept 2021 - Jan 2022
70	Syria	Akkad & Mouselli	2023	Qualitative	During Covid Pandemic
71	Tanzania	Shao *et al.*	2022	Qualitative	Feb 2020 - Feb 2021
72	Thailand	Sastararuji *et al.*	2022	Qualitative	August 2020
73	Tonga	Faasolo & Sumarlia	2022	Quantitative	May–July 2021
74	Trinidad & Tobago	Mohan *et al.*	2021	Quantitative	2015
75	Tunisia	Bellakhal & Mouelhi	2023	Quantitative	March 2013 - July 2014
76	Turkey	Uzkurt *et al.*	2023	Quantitative	Oct - Dec 2021
77	Uganda	Eton *et al.*	2021	Quantitative	2018
78	Ukraine	Rodchenko *et al.*	2021	Quantitative	Nov 2020-Feb 2021
79	Uruguay	Bianchi & Machado	2021	Quantitative	2009 - 2015
80	Uzbekistan	Tuychiev	2022	Qualitative	During Covid Pandemic
81	Vietnam	Nguyen *et al.*	2022	Quantitative	NA
82	Yemen	Al-Hakimi *et al.*	2021	Quantitative	NA
83	Zambia	Nan & Park	2022	Quantitative	Sep 2019 - March 2020
84	Zimbabwe	Kaondera *et al.*	2023	Quantitative	2022

NA: We did not find the study periods

Considering Company Size, Level of Responsibility, and Employee Age for Analysing Countermeasures against Barriers to Digital Transformation

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Abstract: Digital Transformation (DT) is gaining traction across all industries. Also, it impacts other sectors, such as non-profit and higher education. DT emerges when connectivity technologies merge with physical assets, potentially affecting value-generating processes and value propositions. These changes will improve effectiveness, business models, and customer relationships. However, firms confront several barriers when they embark on their DT journey. Thus, it is essential to understand how the barriers can be tackled by countermeasures. Understanding the qualities of these countermeasures is critical for businesses to overcome barriers. Thus, this current study searches for similarities and differences across socio-demographic categories representing company size (LE, MLE, SME), level of responsibility (executive, with and without personal responsibility), and age (under 30, 31-40, 41-50, above 50). Data from online surveys revealed 1171 participants' statements. These were used to extract four dimensions and 39 countermeasures. The most prominent countermeasure dimensions are Human and Organisation. The most prominent countermeasures relate to the education of employees in the form of demand-oriented training and benefits and needs of DT. This research adds to identifying similarities across categories and paves the way for greater generalizability of countermeasures.

Keywords: Digital Transformation, Barriers, Countermeasures, Socio-Demographic Analysis

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Introduction

The advancements of digitalisation fuel the digital economy, which is based on producing economic output through developing and operating digital business models (Jallouli *et al.*, 2022). The relationship between digitalisation and value creation has fuelled its further development into digital transformation (DT). Through DT, the interaction of information and communication technologies has revolutionised processes and workflows. As a result, this transition was characterised as a trend that brought about considerable changes in "traditional ways of doing business by redefining processes and relationships" (Dehning *et al.*, 2003). According to this viewpoint, DT includes technology and software solutions that enable advancements in strategy and business models, procedures, and consumer interaction. The discipline of DT crosses with the discipline of Information Systems (IS) (Laudon & Laudon, 2020).

DT enables better servitisation by combining smart goods and services (Kagermann *et al.*, 2013). The development of digital platforms and facilities for capturing real-time data leads to process optimisation and the creation of new business models (Benlian *et al.*, 2015). As a result, chances for gains in efficiency, productivity, competitiveness, and customer interactions through DT are high (Schwab, 2017). DT changes working environments, improving employee functions and competences (Kagermann *et al.*, 2013). Thus, DT serves as a premier foundation for competitive advantages. It accelerates the expansion of digital pioneers, increasing stakeholder value and profit (Gnamm *et al.*, 2018).

However, taking these chances is not simple. Companies have challenges in realising the promise of DT (Hess *et al.*, 2016). In practice, there are various hurdles to the acceptance, dissemination, and development of reengineered and digitalized processes, as well as changed business models (Hirsch-Kreinsen, 2016). As a result, organisations may underestimate the work required to nurture digital innovation (Hadjimanolis, 2003). Corporations will fail to achieve their DT potential if they do not recognise and address these hurdles (Vial, 2019).

Studies that report failure factors are less prevalent than those that indicate success factors (Hadjimanolis, 2003). Thus, this study intends to develop the literature further by concentrating on solving failures that may slow, stop, or disrupt the DT process. This study regards these failures as barriers (Vogelsang *et al.*, 2019). The nature, causes, and stakeholders of these barriers must be acknowledged. Otherwise, countermeasures needed to lessen the adverse impacts cannot be determined. We define countermeasures as activities that can potentially change the nature of, reduce, or dissolve barriers. Only a few digital readiness and maturity models currently guide overcoming such barriers (Jones *et al.*, 2021). At the same time, there is a dearth of understanding about the impact of the recommended

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countermeasures. So far, efforts have focused on the first steps towards a more systematic approach. This study requires a socio-demographic perspective on the perception of barriers and countermeasures to build stakeholder-specific responses in the following stage. Thus, the authors set the following research question for this contribution: How differently do socio-demographic characteristics influence the perception of countermeasures against barriers to DT in companies?

This current research looks at how countermeasures are seen based on firm size, the amount of responsibility associated with the job function, and the ages of the participants. This study adds to a broader debate on countermeasures in the IS community. This research uses a systematic technique to analyse countermeasures related to socio-demographic categories. As a result, it sets the framework for possible models of impact between the analysed traits. Based on the current research results, firms can predict barriers and design effective countermeasures to ensure successful DT. Furthermore, these findings would enhance readiness and maturity models. These findings may better tailor these models to various kinds of businesses and employment categories.

The authors used the following procedures to address the research challenge. The following background section summarises previous work regarding the relationship between DT, barriers, countermeasures, and socio-demographics. The Method section describes the qualitative data collection, sample characteristics, and study strategy. The Results section investigates the perceptions of countermeasures regarding participant characteristics. After, the Discussion section relates aspects of results to each other and to other scholarly work. Finally, the article concludes, including the limitations of the research and future research possibilities.

Literature Review

In recent years, there has been a surge in interest in DT research and practice. Comprehensive definitions of DT include “a process that aims to improve an entity by triggering significant changes to its properties” (Vial, 2019) through the use of various technologies. Other definitions emphasise improved offers through digital services and goods, while also improving the customer experience through digitised processes (Reis *et al.*, 2018); or connect the term to change, innovation and radical improvement (Gong & Ribiere, 2021). All these enhancements were specifically associated with value creation, organisational structure, and financial distribution (Hess *et al.*, 2016). DT becomes highly sophisticated due to orchestrating all of these advancements into value offers, making it difficult to manage their requirements (Pabst von Ohain, 2019). DT and IT-enabled organisational transformation (ITOT) are not interchangeable terms. DT defines new value propositions, whereas ITOT

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supports existing concepts (Wessel *et al.*, 2021). Still, ITOT is comparable to DT in its use of digital resources to generate value (Bharadwaj *et al.*, 2013). The number of barriers increases more in DT than in ITOT as new definitions of value propositions get more sophisticated. Leadership or environmental factors are frequently the source of barriers (Hadjimanolis, 2003). Managers must overcome the barriers, since DT is unavoidable. They can overcome these barriers by recognising how to blend physical and digital elements effectively. Furthermore, because DT barriers are complex constructs, managers should employ a comprehensive DT strategy, including countermeasures. This study defines countermeasures as interrelated socio-technical activities toward overcoming the DT barriers to proceed with the DT process.

The authors did a systematic literature review (Webster & Watson, 2002) to analyse prior study results on barriers to DT on Scopus, EBSCO, and AIS Electronic Library. Search strings containing the keywords "digital transformation" AND "barriers" with their synonyms were used to direct the review. The search yielded 562 papers (not including duplicates). Following the initial screening for relevance and full-text availability, 148 articles were discovered. After multiple in-depth qualitative controls, 99 appropriate studies were selected for further inspection (Varwig *et al.*, 2021). A second search adding the keyword "solution*" and its synonyms yielded 120 papers. Scanning the titles for relevance yielded 25 papers taking a holistic perspective on overcoming barriers to DT in a corporate context, which aligns with this research. Thus, papers focusing on overcoming single barriers (e.g., blockchain technology) or on single solutions (e.g., agile practices) were excluded, as such studies frequently have poor generalisability. As a result, this study did not concentrate on specific technology. Instead, the purpose of this study was to investigate differences between traits. The ability to compare these traits across socio-demographic categories allows for the differentiation of specific and general implications. As a result, this comprehensive study may lead to a higher generalisability (Sarker *et al.*, 2019). The higher number of studies on defining barriers and the smaller number of studies on overcoming them demonstrates the importance of the field and its need for further development.

Most barrier literature identified technological difficulties (Bilgeri & Wortmann, 2017). Certain research used interpretative approaches and classified barriers based on internal and external perceptions (Henriette *et al.*, 2016), whereas others used temporal approaches based on short-term orientation and tactics (Kumar *et al.*, 2021) or enterprise sizes (Khanzode *et al.*, 2021). Further research focused on more organised approaches that used interpretive structural analysis to model inter-barrier connections (Abdul-Hamid *et al.*, 2020; Agrawal *et al.*, 2019; Karadayi-Usta, 2020). Fewer studies offered suggestions or actions for addressing these barriers. Some even identified a vast range of countermeasures but still focused on a specific area of application, e.g., drafting shoestring projects in small and medium-sized enterprises (SMEs) in the construction industry (Yilmaz *et al.*, 2023) or low-cost digital solutions for the operations management of SMEs (Macias-Aguayo *et al.*, 2023). The manufacturing industry is a prominent candidate for research ranging from evaluating single cases to assessing path dependencies (Brekke *et al.*, 2023) and giving EU-wide policy recommendations for the manufacturing industry (Senna *et al.*, 2023). Further works studied the strategies of digital champions in government agencies (Wilson & Mergel, 2022) or generated roadmaps as part of the countermeasures (Shahi & Sinha, 2021). Often, such works rarely considered the multidimensional interdependence of barriers and recommendations. Examples of work including multidimensional interdependences embraced educational facilities to boost employee knowledge (Westerman *et al.*, 2011) and external technical expert requirements of IoT deployment with systemic difficulties (Zaychenko *et al.*, 2021), which needed complex causality investigation. Previous studies that identified barriers used technology-enhanced business models, improved customer contact, or operational organisation as a methodological lens (Dremel, 2017).

Socio-Demographics

For companies to succeed in their DTs, employees must have a digital mindset (DM). DM refers to employees' beliefs, attitudes, and perceptions towards technological change and digital transformation initiatives. It encompasses their willingness to adopt and embrace digital technologies, openness to change, and ability to adapt to new digital working methods. Several factors influence employees' digital mindsets, including organizational culture, leadership support, training and education, perceived personal benefits and risks, and organizational communication and collaboration (Solberg *et al.*, 2020).

Based on these factors, this study evaluates the socio-demographics of company size, level of responsibility, and employee age. The company size relates to employees' perception of culture and communication. Depending on the level of responsibility, managers actively provide leadership support and shape organizational communication, whereas other groups of employees have a more passive role and are led. Employees of different ages will have different needs for training, but also different perceptions of benefits and risks for their personal careers. Thus, the authors deem these categories to be highly relevant for an analysis.

SMEs and LEs

Advancing in DT is the ambition of every sector, not just tech. titans. DT is essential for firms to compete in a digitally connected and ever-changing business world. With each DT step, companies may increase their digital advantage. DT affects SMEs (Skare *et al.*, 2023); along with other issues like funding, innovation, entrepreneurship (Wonglimpiyarat, 2015) and hiring qualified workers (Duan *et al.*, 2002). Internationalisation and digitalisation are common challenges for SMEs (Lu & Beamish, 2001; Tarutė *et al.*, 2018). DT for SMEs transforms the competitive landscape, introduces new technology, develops digital skills, and requires new leadership (Skare *et al.*, 2023). DT alters SMEs' business models and customer value creation (Matarazzo *et al.*, 2021). In addition to the greatest inflation rate in over a decade, SMEs have digital leadership barriers. One issue with SME leadership is the lack of formal qualifications compared to larger enterprises (LEs). Rather, SME executives learn on-site (Bolden & Rohini, 2020). In addition to the qualifications, talents, and skills to teach and develop people, leaders need technical and managerial competencies to adapt to a changing environment. Given the multiple barriers of applying DT while leading people, many SME leaders may fail due to skill gaps. A DT requires strategic hiring by leaders. SMEs struggle to find skilled workers, which hinders their operations. The lack of human resources with the knowledge and skills to meet DT standards is a major barrier to DT in SMEs (Nguyen *et al.*, 2015). Keeping up with digital marketing innovations is a capability challenge. Focusing on historical methods may squander effort. DT greatly impacts marketing, enabling new avenues for understanding client and customer behaviour, such as the placement of personally tailored ads using algorithms and data collection (Hausberg *et al.*, 2019).

LEs face barriers due to their size. One of the most common barriers they face is the complexity of monitoring performance in all business areas. They must choose the right key performance indicators (KPIs) to provide the business with insights into success or failure. Most business people are not experts in developing these KPIs but must understand their implications (Veleva, 2009). However, enhanced digitalization can make KPIs more reliable, collect real-time data, and evolve into Business Activity Monitoring (Wetzstein *et al.*, 2008). Moreover, LEs' complex structures can hinder innovation and change. They tend to have a more articulated list of desired outputs compared to SMEs, making it more difficult to align with change or innovation and find a suitable balance between exploration and exploitation (Del Vecchio *et al.*, 2018). Another challenge for LEs is that they work in silos, meaning different departments or business units work almost individually without adequate coordination. At best, these silos provoke specialization and make the work more effective. At worst, they can create a mentality where the departments are so separated that they do not share any knowledge or collaboration and only work towards their own department goals. Thus, a silo mentality might prevent corporations from making achievements (de Waal *et al.*, 2019).

Responsibility level

DT impacts management at all levels. Thus, it calls for rediscovering leadership requirements (Henderikx & Stoffers, 2022). Especially, middle managers play a crucial role in implementing digital strategy and can influence the success or failure of DT projects (Christodoulou *et al.*, 2022). Naturally, top managers contribute to companies' DT by understanding digitalization, setting the formal context, and leading the change (Wrede *et al.*, 2020). Interestingly, the COVID-19 pandemic has made public managers more confident in information and communication technology capacity, regardless of their level of responsibility (Barrutia & Echebarria, 2021). Factors influencing managers' perception of DT include rising competition, changes in business models, and new digital competences (Syaglova & Maslevich, 2021), as well as globalization processes and innovative technologies (Astafeva *et al.*, 2020). Managers perceive pressure from digitalization. Generally, it has neither been associated with psychological well-being nor shown an effect on managerial experience, managerial responsibility, or age (Zeike *et al.*, 2019).

Employee age

Further exploring relationships between DT and age, younger employees show a stronger inclination toward motivational factors and perceive higher techno-stress levels than older employees (Kluge *et al.*, 2019). Older employees tend to have more negative attitudes toward DT due to less tech-savviness (Eickemeyer *et al.*, 2021) and are more pessimistic regarding the change provoked by DT (Heim & Sardar-Drenda, 2021). Generally, employees' beliefs about technological change and their digital mindsets can impact their engagement or withdrawal from their company's DT initiatives (Solberg *et al.*, 2020). Also, employees' perceptions of DT change over time and are influenced by barriers experienced during the change journey (Van Der Schaft *et al.*, 2022). Employees fear being replaced by digital technologies, potentially impacting their competitive advantages and job prospects (Liu *et al.*, 2022). Further, fears stem from increased work demands and limited resources resulting from the hasty implementation of digital technologies, leading to DT stress (Leo *et al.*, 2023). Lastly, employees are concerned about DT's impact on their psychological needs, such as autonomy, competence, and relatedness, and how it may affect their performance, satisfaction, and well-being (Makowska-Tłomak *et al.*, 2022).

Method

To tackle the research problem, the authors collected data through interviews and, based on their results, an online survey was set up. Following a pre-study design, a barrier model following a socio-technical view was constructed using triangulation (Brink *et al.*, 2022). This

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current study was conducted based on the data from an anonymous online poll to obtain additional qualitative data. Participants were asked open-ended questions about their perceptions of the three most important barriers and ways of overcoming them.

The authors aimed to recruit a diverse sample to broadly analyse the field (Yin, 2014). In a first round, 340 participants were recruited through calls to personal and professional contacts on social networking sites. While non-random sampling is an acceptable method for exploring a domain, it might result in bias (Stern *et al.*, 2017). As a result, additional participants from four companies that replied to social network calls were included. This data collection step used a random sampling strategy. As a result, an additional 185 people willingly completed the same poll. In total, between December 2019 and April 2021, 525 completed surveys were collected using additional random and non-random sampling. The bulk of participants (60%) were from German-speaking countries. The sample included participants from European and non-European countries (e.g., Türkiye and the United States), resulting in cross-national data. Table 1 shows the dominance of the automotive sector and SMEs. Furthermore, most participants have no responsibility for staff. Many of them are under the age of 31.

Table 1. Questionnaire sample (N=525)

Criteria	Attribute [Relative share of participants]
Sector	Automotive [18%] | Wholesale [16%] | Finance & Insurance [14%] | Construction [13%] | Mechanical & plant engineering [9%] | Food [7%] | Information and communications technology [3%] | Other [20%]
Position	Manager [6%] | With personnel responsibility [26%] | Without personnel responsibility [59%] | Other [9%]
Employees	>= 1,000 [35%] | 250-999 [17%] | 0-249 [45%] | Not specified [3%]
Age	<31 [33%] | 31-40 [20%] | 41-50 [19%] | >50 [17%] | not specified [11%]

The authors analysed 1171 statements on how to overcome barriers through countermeasures. As no initial model for overcoming was available, the authors coded (Mayring, 2014) and aggregated the statements into countermeasure dimensions openly (Azungah, 2018). Then, they invited colleagues to discuss and aggregate the codes to identify adjusted dimensions and attributes. As a result, they followed rules to ensure credibility (Nowell *et al.*, 2017). They oriented the clustering toward the TOE [Technology–Organization–Environment] framework (Baker, 2012) with an additional Human dimension for these dimensions. Afterwards, the frequencies of the countermeasures according to their socio-demographic categories were calculated by relating the amount of how often a countermeasure was coded to the total number of statements in a category. The frequencies of alleged DT countermeasures were analysed according to socio-demographic groups: company size, level of responsibility associated with the job role, and employees' ages in the second stage. This study classified three types of company categories: fewer than 250 employees (small and medium-sized enterprises, SMEs), 250 to 999 employees (medium to large enterprises, MLEs), and more than 999 employees (large enterprises, LEs). Further, three duty levels were identified: executives, employees with personnel responsibility (w/ PR), and employees without personnel responsibility (w/o PR). Also, the employees' ages were classified as: younger than 31; between 31 and 40; 41 to 50; and older than 50. This study surveyed age-related experience rather than professional experience. As age includes study time, the authors considered it a suitable surrogate for general experience. Table 2 reports the relative shares of the relevant DT countermeasures by socio-demographic group.

Results

Table 2 (in four parts: a, b, c, and d) shows the different frequencies for the socio-demographic groups regarding the four countermeasures' dimensions and their 39 characteristics.

Table 2. Countermeasures on Barriers to DT regarding company size, position, and age

a. Dimension: Human

Countermeasure	Company Size			Position			Age			
	LE	MLE	SME	Exec.	w/ PR	w/o PR	< 30	31-40	41-50	> 50
Accelerating decision-making	0.4%	0.6%	0.6%	0.0%	0.0%	0.8%	0.8%	0.4%	0.4%	0.0%
Thinking with foresight	0.2%	0.6%	1.3%	0.0%	0.9%	0.8%	0.5%	2.1%	0.0%	0.5%
Developing a clear DT roadmap	1.8%	2.3%	1.5%	2.9%	1.8%	1.6%	2.3%	1.7%	1.3%	1.4%
Providing transparency over the transformation process	3.8%	2.3%	2.4%	7.4%	2.7%	2.7%	0.8%	3.0%	5.1%	2.9%
Educating about the benefits and needs of DT projects	11.3%	13.1%	13.3%	7.4%	9.9%	14.1%	12.4%	13.5%	12.0%	13.5%
Promoting open communication and creating transparency	2.9%	5.1%	4.3%	4.4%	4.2%	3.8%	3.9%	2.1%	5.1%	6.3%
Involving and motivating employees	1.8%	10.2%	2.1%	2.9%	3.3%	3.3%	2.8%	2.1%	3.4%	5.3%
Being open minded for changes	2.0%	2.3%	1.5%	0.0%	1.2%	2.3%	2.3%	1.3%	2.1%	1.4%
Engaging staff to realize own ideas and projects	2.4%	1.1%	2.8%	0.0%	3.9%	2.0%	2.6%	3.4%	2.6%	1.9%
Creating capacity among employees	0.4%	0.0%	0.6%	0.0%	0.3%	0.5%	0.3%	0.4%	0.9%	0.5%
Conducting skills gap analysis	1.1%	0.6%	0.6%	0.0%	0.6%	1.0%	0.8%	0.4%	1.7%	0.5%
Offering or intensifying demand-oriented employee training	21.5%	16.5%	18.9%	22.1%	17.4%	19.9%	20.9%	18.1%	17.5%	16.9%
Using external expertise	0.9%	1.7%	2.1%	2.9%	1.2%	1.6%	2.1%	1.3%	2.1%	0.5%
Recruiting or providing suitable staff	7.8%	9.7%	7.5%	4.4%	8.7%	7.9%	7.7%	9.3%	6.4%	7.7%
Rejuvenating workforce	4.4%	2.3%	2.4%	2.9%	5.1%	2.3%	3.1%	5.1%	0.9%	0.5%
Overall	**62.7%**	**68.2%**	**61.8%**	**57.4%**	**61.1%**	**64.8%**	**63.1%**	**64.1%**	**61.5%**	**59.9%**

Countermeasures addressing Human factors receive the highest overall score across all socio-demographic groups, ranging from 57.4% to 68.2%. At the same time, the Human dimension contains 15 characteristics. Looking at the averages across all sociodemographic groups, they range from 3.8% to 4.5%. Within the Human dimension, two characteristics stand out: "Educating about the benefits and needs of DT projects" and "Offering or intensifying demand-oriented employee training". Their values show an increase with decreased company

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size, ranging from 11.3% for LEs to 13.3% for SMEs. Within responsibilities, there is a rather different perception between executive managers (7.4%) and employees w/ PR (9.9%) and w/o PR (14.1%). The age groups between 31-40 and above 51 have a similar perception of the usefulness of education on the benefits and needs of DT (13.5%), whereas the age groups under 30 and 41-50 show a common perception (12.4% and 12.0%, respectively). For the characteristic of "Offering demand-oriented training" concerning company size, the frequency of LEs shows the highest value (21.5%). SMEs sense this characteristic as a less valid countermeasure (18.9%), whereas MLEs show an even lower value (16.5%). Executives perceive it as an essential countermeasure. Employees w/ and w/o PR show lower perceptions (17.4% and 19.9%, respectively). Interestingly, the view on the importance of this countermeasure declines with age (from 20.9% to 16.9%). Other necessary countermeasures from the Human dimension are "Recruiting or providing suitable staff" with values of 7.7% on average. The executives value the importance of this countermeasure with 4.4%.

The dimension Technology contains five countermeasures with an overall value ranging from 2.9% to 15.2%. Technology is the dimension with the highest spread in overall frequencies. The countermeasure with the highest perception is "Extending or modernizing IT-Systems". Its values decrease with increased company size (from 8.6% for SMEs to 5.5% for LEs). The same pattern shows for the responsibility level: the higher the level of responsibility the lower the frequencies for the extension/modernization of IT systems (from 8.6% for employees w/o PR to 2.9% for executives). Regarding age, the age group 31-40 displays the highest value in judging an extension/modernization as an appropriate countermeasure (11%), whereas the oldest age group displays the lowest frequency (5.5%). Interestingly, the countermeasures related to data collection, analysis, and cyber security are perceived as less critical.

Table 2. Countermeasures on Barriers to DT regarding company size, position, and age

b. Dimension: Technology

Countermeasure	Company Size			Position			Age			
	LE	MLE	SME	Exec.	w/ PR	w/o PR	< 30	31-40	41-50	> 50
Extending or modernizing IT systems	5.5%	7.4%	8.6%	2.9%	5.7%	8.4%	6.4%	11.0%	7.7%	5.3%
Harmonizing IT Infrastructure with uniform soft-/hardware and sufficient user licenses	2.0%	3.4%	1.9%	0.0%	3.0%	2.0%	1.0%	2.1%	2.1%	4.3%
Collecting and analyze data	0.9%	0.0%	1.3%	0.0%	1.2%	1.1%	1.0%	0.4%	1.3%	1.4%
Ensuring data security	1.8%	0.0%	1.3%	0.0%	2.1%	1.1%	1.8%	0.4%	2.1%	1.4%
Designing simple and intuitive systems	0.7%	0.0%	0.7%	0.0%	0.9%	0.4%	0.3%	1.3%	0.9%	0.0%
Overall	**10.9%**	**10.8%**	**13.9%**	**2.9%**	**12.9%**	**13.1%**	**10.6%**	**15.2%**	**14.1%**	**12.6%**

The dimension Organization contains 15 countermeasures with an overall average frequency of 20.4%, leading to an average frequency per countermeasure of 1.4%. The countermeasure "Releasing or increasing a separate budget for DT projects" indicates the highest sum of frequencies across all socio-demographic classes (56.1%) followed by “Conducting (long term) cost-benefit analyses” (23.1%) and “Promoting cross-functional collaboration (in the form of working groups or job rotation)” (22.9%). MLEs perceive the DT budgets as a less valid countermeasure (4.0%) than LEs and SMEs (5.5% and 5.1%, respectively). Among executives, it is perceived as more critical (10.3%) than among employees w/ PR (7.5%) and w/o PR (3.5%).

The age groups under 30, 31-40, and above 50 display frequencies of around 4%, whereas the age group of 41-50 perceive the budget for DT projects as a more dedicated countermeasure (7.7%). Regarding cost-benefit analyses, LEs (3.3%), employees w/ PR (3.6%), and the age group above 50 (3.9%) display high values in their socio-demographic class. The promotion of cross-functional collaboration is of higher interest for SMEs (2.8%), executives (2.9%), and the age group 41-50 (3.4%).

Table 2. Countermeasures on Barriers to DT regarding company size, position, and age

c. Dimension: Organisation

Countermeasure	Company Size			Position			Age			
	LE	MLE	SME	Exec.	w/ PR	w/o PR	< 30	31-40	41-50	> 50
Releasing or increasing a separate budget for DT projects	5.5%	4.0%	5.1%	10.3%	7.5%	3.5%	4.4%	4.2%	7.7%	3.9%
Prioritizing investments in DT	2.2%	0.0%	1.7%	2.9%	1.8%	1.2%	2.6%	1.7%	0.0%	1.0%
Conducting (long term) cost-benefit analyses	3.3%	1.1%	1.3%	2.9%	3.6%	1.4%	1.3%	2.5%	1.7%	3.9%
Taking advantage of financial support from the state	0.4%	0.6%	0.4%	0.0%	0.6%	0.4%	1.0%	0.0%	0.0%	0.0%
Streamline organizational processes	1.6%	1.7%	2.8%	0.0%	1.8%	2.2%	3.1%	0.8%	3.4%	0.0%
Flattening and simplifying organizational structures	2.0%	1.1%	1.1%	1.5%	1.2%	1.6%	1.8%	1.3%	1.3%	1.9%
Increasing scope for decision-making in lower levels	1.1%	0.0%	1.3%	1.5%	0.3%	1.4%	0.8%	1.7%	0.0%	1.4%
Implementing IT Support	0.2%	2.3%	0.0%	0.0%	0.3%	0.5%	1.0%	0.0%	0.0%	0.5%
Centrally coordinating DT projects	1.3%	0.0%	0.2%	0.0%	0.0%	0.8%	0.3%	0.4%	2.1%	0.0%
Defining clear DT responsibilities	1.1%	1.1%	1.1%	0.0%	0.9%	1.4%	1.0%	1.3%	0.4%	1.9%
Promoting cross-functional collaboration (in the form of working groups or job rotation)	1.3%	2.3%	2.8%	2.9%	2.4%	2.0%	2.1%	1.7%	3.4%	1.9%
Implementing agile project management and design methods	0.7%	1.1%	0.4%	1.5%	0.9%	0.4%	0.8%	0.4%	0.9%	0.0%
Providing improved working conditions	0.4%	0.0%	0.0%	0.0%	0.0%	0.3%	0.3%	0.0%	0.0%	0.0%
Moving customers to the centre of attention in the development of solutions	0.7%	0.6%	0.7%	1.5%	1.5%	0.1%	0.8%	0.4%	0.9%	1.0%
Simplifying and expanding customer touchpoints	0.4%	1.1%	0.4%	0.0%	0.3%	0.7%	1.0%	0.0%	0.0%	1.0%
Overall	**22.4%**	**17.0%**	**19.3%**	**25.0%**	**23.1%**	**18.0%**	**22.2%**	**16.5%**	**21.8%**	**18.4%**

The Environment dimension contains four countermeasures ranging from 2.6% to 14.7% on their overall frequency values. The most prominent countermeasures are “Promoting the broadband rollout” and “Expanding partnerships with external parties” with sums across all socio-demographic groups of 20.9% and 19.8%. Expanding partnerships are highly frequently reported by the group of executives (8.8%) and the age group above 51 (3.4%). Also, the promotion of broadband roll-out is favoured by the executives (4.4%) and the age group above 50 (3.4%). Compliance with data protection regulations seems out of scope as a countermeasure.

Table 2. Countermeasures on Barriers to DT regarding company size, position, and age

d. Dimension: Environment

Countermeasure	Company Size			Position			Age			
	LE	MLE	SME	Exec.	w/ PR	w/o PR	< 30	31-40	41-50	> 50
Expanding partnerships with external parties	1.3%	1.7%	0.9%	8.8%	0.3%	0.8%	0.8%	0.8%	0.9%	3.4%
Lobbying	1.6%	1.1%	0.9%	1.5%	0.6%	1.5%	2.3%	0.0%	0.4%	1.9%
Promoting the broadband rollout	0.9%	1.1%	2.8%	4.4%	1.8%	1.6%	1.0%	3.0%	0.9%	3.4%
Complying with data protection regulations	0.2%	0.0%	0.4%	0.0%	0.3%	0.3%	0.0%	0.4%	0.4%	0.5%
Overall	**4.0%**	**4.0%**	**5.1%**	**14.7%**	**3.0%**	**4.2%**	**4.1%**	**4.2%**	**2.6%**	**9.2%**

Discussion

This current study continues research on the socio-demographics of barriers to DT (Packmohr *et al.*, 2023) and into countermeasures, using the same characteristics of organization size, responsibility, and personnel age. As for the barriers, seven broad dimensions were identified: Missing Skills, Technical Barriers, Organizational Misalignment, Corporate Culture, Structural Mismatch, Regulatory Restrictions, and Market Restrictions. Each dimension contains between three and five characteristics, adding up to 29. As for the countermeasures, four broad dimensions were identified, comprising Human, Technology, Organization, and Environment. In total, they contain 39 specific countermeasures.

Corporate Culture and Structural Mismatch are the most common barrier dimensions (Packmohr *et al.*, 2023). Within the countermeasures, Human and Organizational dimensions are of utmost importance. Several countermeasures might directly affect Corporate Culture, such as transparency, open communication and being open-minded for change. If openness becomes a part of the culture, it might spill over into technical areas such as integrating open data flows into operations, which in turn can improve business models (Antonova & Yordanova, 2017). To the contrary, openness will increase security issues, hindering a DT (Stewart, 2023). Ensuring transparency in the digital environment is essential, as it enables self-organization, costless coordination, and agile response, which fuel digital transformation (Ulieru & Verdon, 2009). Countermeasures for Structural Mismatch might be found in the dimension of Organization, such as streamlined processes and flattened organization. Speed and collaboration can be achieved by decreasing hierarchical levels, decentralising decision-making, and improving employee collaboration. Traditional organizational models based on bureaucracy are inflexible and not viable for the new market conditions. Thus, there is a need for new forms of organizational structures (Mirković *et al.*, 2019).

Concerning LEs, Corporate Culture is viewed as the most fundamental barrier (Packmohr *et al.*, 2023). Explicitly working on further educating employees on DT's particularities and an openness to change is an adequate countermeasure. Still, employees fear losing clients, productivity, and employees due to ineffective digital workplaces (Hamburg, 2020), which further education could draw upon. Also, Technology countermeasures could be implemented to deal with employees' fears. To address cultural change, scholars recommend a reflective approach emphasizing consistency and expressiveness (Alvesson & Sveningsson, 2015).

LEs tend to have more rigid hierarchies than SMEs, hindering a DT. Looking at the countermeasures, the dimension Organization holds some advice: especially, LEs gain from conducting (long-term) cost-benefit analyses and increasing the scope for decision-making in lower levels. Tools like Balanced Scorecard have been utilized to manage organisational structures (Kaplan, 2009) and adopted in a DT background (Yamamoto, 2020). Remarkably, the Balanced Scorecard provides the possibility to facilitate double-loop learning (Li *et al.*, 2021), enabling managers to enhance their mental models toward a digital business system.

LEs are often publicly listed, which provides them with a broader range of financing options (Eggers, 2020). Thus, they are less prone to barriers from financial resources. Still, releasing or increasing a separate budget for DT projects, prioritizing investments in DT, and conducting (long-term) cost-benefit analyses are more prominent countermeasures in LEs. Even if bureaucracy is seen as a hindrance for DT (Mirković *et al.*, 2019), these results indicate that a certain degree of bureaucracy might be beneficial. A more formal approach could help MLEs and SMEs better guide their work toward a DT, e.g., with formalised shoe-string projects (Yilmaz *et al.*, 2023).

Offering or intensifying demand-oriented employee training is a prominent countermeasure across all company types. Still, LEs stand out. This is surprising as it is a solution to the scarcity of personnel resources, which is pronounced more in MLEs and SMEs (Eller *et al.*, 2020). At the same time, MLEs are more proactive in recruiting or providing suitable staff. MLEs and SMEs could attract talent by offering a more personalised work environment and individual career paths. LEs could overcome a lack of personnel resources by allocating more financial resources. Instead, SMEs engage more staff to realize their ideas and projects. Keeping up with legal regulations is more challenging for SMEs due to limited resources (Sirur *et al.*, 2018). They often operate on a local scale or in specific markets (Dosi *et al.*, 2015), which gives them slightly better means to cope with market regulations. Still, SMEs are not very fond of expanding partnerships with external parties. Instead, a better broadband connection is a

http://doi.org/10.18080/jtde.v12n1.857

countermeasure within the environmental dimension. Of course, DT is based on connectivity technologies (Vial, 2019). To a certain extent, the technical infrastructure seems missing in SMEs, which is indicated by a higher overall need for technical countermeasures.

Shaping the corporate culture falls under the responsibility of the executives and employees w/ PR (Gurzhii *et al.*, 2019). Looking at the countermeasure dimension Human, employees w/o PR value these more. As they perceive an aggravated problem, they are more prone to seeing solutions. Thus, executives could use this as a source for creative countermeasures. Especially, the workforce w/o PR is more open to further education.

A prominent countermeasure for executives to tackle the lack of personnel resources is demand-oriented employee training. Also, they see more opportunities to expand partnerships with external parties, as their role requires a strategic perspective (Drucker, 2017). Given their responsibilities within companies (Kane *et al.*, 2017), it coincides with a low perception of the usage of technical countermeasures on the executives' side.

Overall countermeasures regarding Human factors are perceived as less necessary in the age group above 50. On the contrary, this age group, together with the age group 31-40, favours the idea of education about the benefits and needs of DT projects. Culture influences employee commitment (Ramdhani *et al.*, 2017). Younger employees may experience more conflict between their generational culture and career goals within the formal structure, leading to a sense of mismatch. It is particularly important to provide Generation Z employees with a realistic job preview to lead their expectations (Schroth, 2019). Thus, the younger age group seeks countermeasures to offering or intensifying demand-oriented employee training. Even, if age has been found to impact the relationship between skills, training, and DT (Trenerry *et al.*, 2021), the older generations see open communication and transparency, as well as involvement and motivation, as more important countermeasures. These factors are more generic than demand-oriented training, indicating that the older generation seeks a broader sensemaking perspective.

Younger employees see less need for technical countermeasures. This might be because they are generally more proficient in the technology (Pînzaru & Mitan, 2016). The age group 31-40 especially sees more need for technical countermeasures. This age group grew up more digitally than the older groups. At the same time, it has been exposed to business problems for a longer time. Thus, they might be able to translate business problems into technical requirements. This is a skill that evolves over time. The research found a technology gap among younger employees, as they show limited skills in using technology to solve business problems (Pfaltzgraf & Insch, 2021).

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Countermeasures related to strategic issues, such as developing a clear DT roadmap, are generally not considered premier among the participants, regardless of the age group. On the contrary, the research findings suggest roadmaps as an essential instrument (Aras & Büyüközkan, 2023). DT is connected to the resource-based view. The resource- and knowledge-based views emphasize the role of resources and capabilities in creating competitive advantage (Adhiatma *et al.*, 2024). To this extent, the participants' impressions overlap in aiming to develop training and culture further to support the resource-based view. In the long run, it might be beneficial to include the market-based view (McGee, 2015) and balancing market- and resource-based views (Makhija, 2003), as DT includes aspects such as closer customer contact and business models (Vial, 2019).

The results of this exploratory study show the importance of countermeasures related to Human factors. This supports other findings emphasizing that DT is primarily concerned with overcoming human barriers (Tabrizi *et al.*, 2019). Thus, countermeasures need to tackle issues related to interaction and communication, which should not be seen internally only. Instead, interaction with external partners will lead to a spillover of DT ideas, thus relating DT to the field of innovation (Stoianova *et al.*, 2022)

Conclusions/Recommendations

The current study answers the question of how differently countermeasures of barriers to DT are perceived according to socio-demographics, such as company size, level of responsibility, and employee age. The most essential countermeasure dimensions are Human and Organisation, containing aspects of training, education and working with dedicated DT budgets.

The current study is systematically conducted. The authors strived for a broad data collection to be able to take a holistic approach. The data collected contains high rates of respondents from the Automotive, Wholesale, Finance & Insurance, and Construction sectors, representing a diverse industrial structure. The sample shows a high rate of participants not belonging to a sector (*cf.* Table 1: 20% Other). The authors deem the risk of bias in this part of the data as low due to the broad calls for participation during the data collection. Also, it is essential to consider that age may be correlated with the level of responsibility; as individuals age and gain experience, their level of responsibility tends to increase. Thus, the socio-demographic criteria might not show independent patterns. This becomes visible when looking at the result of the countermeasure dimension Environment in which Executives and the age group 50+ show high frequencies (14.7% and 9.2%).

These holistic results can help inform further studies evaluating causalities between countermeasures and barriers to evaluate effect sizes. The high-influence and still broad countermeasures could be broken down into specific actions. For example, further studies could clarify the deeper meaning of Offering or intensifying demand-oriented employee training or how to organize these. AI systems might help in customizing individual pieces of training that are aligned with individual expertise and company goals.

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ICT as a Determinant of Happiness

Cross-Country Evidence

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Abstract: This study aims to investigate ICT as a determinant of happiness. This study shifts its focus from traditional metrics to subjective assessments and extends the role of ICT to happiness research at the cross-country level. Due to innovations, the role of ICT may not be limited to productivity, consumption patterns, and consumer behaviour. A panel dataset for 40 countries with higher subjective wellbeing representing all continents from 2006 to 2019 is used. The pooled mean group (autoregressive distributed lag, ARDL) approach signifies that ICT is a determinant of happiness. Moreover, this research also investigates how effective governance negatively relates to happiness, and how human progress and economic development positively impact happiness. This research argues that policymaking should shift from the traditional economic development approach to socio-technical wellbeing.

Keywords: Innovation, Wellbeing, Governance, Human Development

Introduction

We are living in an era of transforming information due to the spread of information and communication technology (ICT). ICT governs various aspects of human life, including education, sports, engineering, management, health, tourism, and the economy. ICTs are used as an instrumental kit for solving problems. Nevertheless, humans underwent diverse technological transformations as a result of industrialization, yet the historical significance of ICT has emerged as complex, encompassing both its widespread adoption and its profound impact (Sala-I-Martín *et al.*, 2012).

Over the past three decades, innovation studies have evolved in diverse directions, with a consistent theme across various research areas: the pivotal role of innovation in fostering

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economic performance. Recently, ICT has improved economic results by increasing capital formation rates, export potential, and financial performance (Juster *et al.*, 1981). As a result of these factors, the GDP ought to be increasing. There are a lot of studies that capture the impact of ICT on economic growth, productivity, trade openness, and governance by using the proxy of investment in ICT (Goldfarb & Tucker, 2019; Dedrick *et al.*, 2011; Mačiulytė-Šniukienė & Gaile-Sarkane, 2014; Oulton, 2012). It is also playing a key role in socio-economic development. It has transformed human lives and left an everlasting impact on wellbeing.

In this context, two schools of thought investigated the impact of ICTs' diffusion. One of them is more optimistic, which builds supporting arguments. In the literature, the old arguments support the position of ICTs' diffusion by the "penalty of taking the lead" (Veblen, 1990). The last few decades showed that the catching-up countries need to invest in ICT-related infrastructure and skills. The diffusion of ICT is more complicated to catch up with developed countries due to the above reasons (Maiti *et al.*, 2020). A less optimistic stance is evident in development research regarding the current prospects for innovation and technology-based growth. Abramovitz (1986) investigated it in historically oriented studies on technological development, growth, and catching up.

Traditionally, wellbeing is measured by gross domestic product (GDP), which has been criticised as a weak indicator and claimed as an unsuitable tool for public policies (Fleurbaey, 2009). Therefore, other statistical tools were introduced for the measurement of wellbeing as complementary to GDP, which was observed by Stiglitz & Fitoussi (2009). Ben Martin (2016) investigated that wellbeing is the most important indicator for innovative research and highlights it in twenty challenges for future research: "Innovation scholars will need to shift the focus of our empirical work from innovation for wealth to innovation for wellbeing" (Martin, 2016).

At the same time, another problem arises: the widespread adoption of ICT necessitates both advanced skill levels and robust infrastructure. This leads to a scenario where affluent nations reap greater advantages from economic disparity, contributing to the widening digital divide (Maurseth, 2020). According to the economic point of view, happiness comes from richness. Research on happiness also indicates this paradox. But the Easterlin *et al.* (2010) paradox has proved that average happiness remains the same even with increasing income. The World Happiness Report (2021) also shows that many countries with high economic growth have a low happiness index.

Thus, the researcher's attention shifted from traditional measures to happiness because the true level of wellbeing is determined by intangible factors (Kyle, 2020). Research shows a positive GDP-happiness link in low-income nations, improving wellbeing. But, at a certain

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level of income, increase in GDP growth yields diminishing happiness gains (Easterlin *et al.*, 2010). At the same time, an elevated GDP can result in heightened income disparity, potentially exerting an adverse impact on the wellbeing of individuals with more modest earnings, irrespective of the nation's overall affluence (Zagorski *et al.*, 2014; Schneider, 2016). Heterogeneities like cultural values, social norms, and expectations can influence how individuals perceive and prioritize happiness. Consequently, these factors force researchers to make a transition from traditional measures to subjective measures. Pursuing economic growth should be balanced with policies that consider the broader aspects of human wellbeing, including social, environmental, and mental health factors.

Therefore, there is a dire need to conduct a study that would make a substantive contribution to the current body of knowledge across various dimensions. The empirical investigation into the ramifications of ICT on happiness using Subjective Well-Being (SWB) as a proxy remains in its nascent stage, primarily owing to a relatively limited emphasis on subjective indices of wellbeing. The previous studies investigating the impact of ICT on SWB used the earlier technologies and a single dimension of ICT, such as TV watching (Graham & Nikolova, 2013; Kavetsos & Koutroumpis, 2011), Internet use (Castellacci & Tveito, 2016; Castellacci & Viñas-Bardolet, 2019; Lohmann, 2015), or mobile phone penetration (Alhassan & Adam, 2021). The mentioned researchers used old happiness survey data that was collected in a low ICT diffused era to check the relationship between ICT and happiness.

To fill this gap, we combine four variables to construct an aggregate ICT index and show the relationship with happiness, which is determined by the ladder wellbeing index. This study addresses all these questions with the Pooled Mean Group (PMG) technique. Moreover, this research study also investigates the impact of effective governance, human progress, environmental development, and economic development on happiness.

The remaining study is structured as follows. The next section delineates a comprehensive literature review on ICT in the context of the transition from conventional measures to subjective wellbeing. The third section elucidates the theoretical underpinnings, while the following section delves into the methodology employed. The fifth section deals with a conclusion and policy implications. The last two sections encompass the research implications, limitations, and future suggestions.

Literature Review

The literature review comprises two distinct segments: the initial section delves into the determinants of subjective wellbeing, while the subsequent one deals with ICT as a path towards subjective wellbeing.

http://doi.org/10.18080/jtde.v12n1.817

Determinants of subjective wellbeing

The literature review aims to explore and synthesize the extensive body of research on the determinants of subjective wellbeing, by examining the diverse range of factors, including ICT, that influence this elusive concept. In this research, the determinants of SWB are corroborated by subsequent studies. The economic determinants of SWB are income (Easterlin *et al.*, 2010; Kahneman & Deaton, 2010), unemployment, inflation, GDP (El Ouardighi & Munier, 2019; Hongo *et al.*, 2020; Welsch & Kühling, 2016), and inequality (Delhey & Dragolov, 2014; Layte, 2012; Oishi *et al.*, 2011). Due to the Easterlin *et al.* (2010) paradox, the relationship between economic growth and SWB ought to be inconclusive.

Further, the effectiveness of the government also affects people's wellbeing and happiness (Shamsi *et al.*, 2018). Empirical evidence examined the positive as well as negative impact of good governance on SWB (Almatarneh & Emeagwali, 2019; Cárcaba *et al.*, 2022; Helliwell & Putnam, 2004). In addition, environment is very important for human beings and it can exert an influence on their wellbeing, as, for example, with climate change, pollution, and weather conditions (Frijters & Van Praag, 1998; Schmitt, 2013). Thus, this study uses a collective index for the environment, economic development, and ICT following the methodology of D'Acci (2011) to check their effect on SWB.

ICT as a path towards subjective wellbeing

Hardy (1980) initially investigated the contribution of ICT to productivity growth. He pointed out the direct impact of telephones on economic growth in 60 selected countries taking 13 years of data and using cross-lagged correlation techniques. In contrast, the Solow productivity paradox shows that the productivity of workers is not enhancing (Solow, 1987). This is the origin of the debate on ICT diffusion and economic growth, which raised the question: Does ICT affect economic growth and wellbeing? A study on the US economy also examined that there was no massive contribution to economic growth between 1970 and 1992 (Oliner & Sichel, 2000).

By contrast, Seo *et al.* (2009) showed the dynamic interdependent relationship between ICT investment and economic growth for a sample of 29 countries in the 1990s. Akinlo (2023) and Haftu (2019) pointed out that the effect of telecommunication infrastructure development has a positive impact on the economic growth of sub-Saharan African countries and the per-capita income of the region, while using panel data for the period 2006-2015. The debate regarding the relationship between ICT and economic growth remains inconclusive, with scholars and experts continuing to examine and evaluate the complex and multifaceted dynamics at play.

http://doi.org/10.18080/jtde.v12n1.817

Consequently, scholars have turned their attention to additional facets associated with the firm's behaviour and consumers' behaviour after economic growth, investment, and ICT nexus. Hjort & Poulsen (2019) used firm-level data from 12 African countries to examine how fast Internet connections enhanced exports, production, and firm entry. They also found that fast Internet connections increased income levels, which in turn raised satisfaction levels. Goldfarb & Tucker (2019) concluded that digital technology affects firms as well as consumers by lowering costs and saving time, respectively. They argued that online marketing (e.g., Flipkart, Amazon, Alibaba), job finding (e.g., Rozee, Jobbnore, Linkedin), and real-estate marketing (e.g., Zameen, Airbnb) leave a noticeable impact on human behaviour and wellbeing. At present, ICT innovations are increasing the productivity of ICT-intensive firms.

Subsequently, another avenue of scholarly inquiry delves into the trajectory of human advancement. A study undertaken by Lee *et al.* (2017) used a seemingly unrelated regression (SUR) model with panel data covering 14 years from 2000 to 2013, encompassing 102 countries, and showed that ICT diffusion is a determinant of global-level human progress. Elgin (2013) used panel data from 152 countries spanning the period from 1999 to 2007 to analyse how the Internet negatively affects the size of the shadow economy.

Recent researchers have investigated how the diffusion of ICT alters consumption patterns, yielding both positive and negative outcomes (Pea *et al.*, 2012). According to Pea *et al.* (2012), ICT catalyzes passive consumption but also exerts a detrimental impact. The advent of ICT has led to a significant upsurge in the consumption of cultural events. Furthermore, the utilization of ICT has been shown to elevate individuals' happiness levels when engaging with such products (Gui & Stanca, 2010). In contrast, it has brought about transformations in work patterns. In the recent past, the majority of people worked in physical offices, whereas today, due to ICT, remote work has become commonplace through various Internet platforms such as Fiverr, Toptal, Guru, and LinkedIn, which not only saves time but also allows individuals to remain close to their families instead of commuting, thereby influencing overall wellbeing.

ICT diffusion not only reshapes consumption and production paradigms but also exerts a profound influence on governance structures, accountability mechanisms, and institutional policies (Androniceanu *et al.*, 2021; Darusalam *et al.*, 2021; Gouvea *et al.*, 2022; Hartani *et al.*, 2020; Hussain, 2023; Kouladoum, 2022; Liu *et al.*, 2021; Mouna *et al.*, 2020; Suardi, 2021). Advancements in mobile device technology enable both businesses and individuals to communicate. These advancements increase transparency, enhance effective governance, and reduce the menace of corruption (Adam, 2020).

The scope of ICT also deepens different spheres of life, such as cultural, behavioural and social. Epstein *et al.* (2011) also concluded that the digital divide increases income inequality. Due to this evidence, Layard (2021) emphasized that income inequality could lead to increased anxiety, tension, stress, and mental depression, and policymakers need to prioritize wellbeing as a criterion. On the contrary, Zhang *et al.* (2014) argued that the Internet provides opportunities to use information in a better way with data availability and data sharing. They also claimed that ICT innovations help provide different services that positively affect individual satisfaction. Sellers and buyers can choose suitable matches by using search engines. People across the world can communicate and interact easily through email, messaging, video calling, texting, social media, and ICT innovations. These things change their feelings, emotions, and sentiments, which influence their subjective wellbeing. Thus, it encourages the use of ICT, which leads to an increase in life satisfaction.

Most research studies have brought attention to happiness and subjective wellbeing under the influence of ICT. Life satisfaction, subjective wellbeing, and material aspirations are also positively affected by TV consumption, as shown in a natural experiment in East Germany (Bruni & Stanca, 2008; Frey *et al.*, 2007; Hyll & Schneider, 2013). On the contrary, Lohmann (2015) argued that ICT has a negative effect, particularly Internet use, on subjective wellbeing. This study used the EU-SILC Survey and World Value Survey data for cross-country analysis. Maurseth (2018) concluded that average happiness is positively related to the ratio of the population of Internet users.

Castellacci & Viñas-Bardolet (2019) argued that Internet technologies increased job satisfaction by enhancing data access, generating new activities, and improving social interactions. They used a bivariate ordered probit model and a hierarchical ordered probit model for cross-country analysis. According to Gupta *et al.* (2019), the impact of ICT advancement on wellbeing is taken into account as the Human Development Index (HDI) using panel fixed-effect modelling. However, Alhassan & Adam (2021) indicated the effect of mobile penetration on the quality of life using data from 114 countries, and applied partial least squares structural equation modelling for results that are not significant on the quality of life.

Recent researchers from various fields, such as Economics and Management, Psychology and Computer Science, have elucidated both the positive and negative impacts of ICT (Internet use, mobile use, broadband use) on life satisfaction and wellbeing. However, the results are multifaceted due to regional, discipline-wise, and societal differences. Gigler (2011) used an alternative evaluation framework by applying Amartya Sen's Capability Approach to study the effects of ICT. He claimed that it enhances the informational capabilities, which improve the social, political, organizational, and cultural dimensions of life. Kavetsos & Koutroumpis (2011) concluded that people with mobile phones, PCs, or Internet access are happier than those who do not have access, based on their analysis of pooled cross-sectional data from

European countries. Innovations in ICT have a positive relationship with subjective wellbeing (Dolan & Metcalfe, 2012). Katz & Koutroumpis (2013) constructed a digitization index using ICT dimensions and the World Dataset of Happiness for cross-country analysis. They argued that digitization is increasing wellbeing.

In the same stream of research, Graham & Nikolova (2013) explored the relationship between ICT and SWB by using the GWP survey panel data for 2009-2011. Ganju *et al.* (2016) examined the role of ICT on a nation's wellbeing with the inclusion of SWB. This empirical study used pooled data across the country and a fixed-effects model to analyse wellbeing through ICT. They argued that using ICT enhances the wellbeing of a country. Sabatini & Sarracino (2017) checked the relationship between social networking sites, and used SWB as a proxy of utility with instrumental variables. They suggested that a social network service has a positive effect on wellbeing. Kawai *et al.,* (2017) investigated national wellbeing by developing gross national happiness rather than gross national product. It was noticed that economic wellbeing is not capturing equal societal welfare.

A study that captured SWB and progress, undertaken by Maiti *et al.* (2020), used an index constructed by D'Acci (2011) and Stiglitz & Fitoussi (2009) to measure the wellbeing and progress in 67 countries, taking into account satisfaction, with six major variables: (1) economic wellbeing; (2) human wellbeing; (3) human progress; (4) cultural progress; (5) environmental wellbeing; and (6) subjective wellbeing through ICT exposure. They employed standard instrumental variable regression methods and simultaneous equation modelling to determine the relationship between them. Their findings showed that ICT exposure enhanced the aggregate level of wellbeing and progress during 2000-2014. The effects of ICT exposure were found to be lesser in developing countries than in developed countries. Contrarily, Aldieri *et al.* (2021) investigated the negative impact of social innovation on subjective wellbeing. They used the instrumental variables regression technique to analyze the results and utilized Veenhoven survey data as a measure of SWB.

The literature survey demands an empirical investigation of the impact of ICT by incorporating all aspects of wellbeing and development, due to its mixed findings. The above studies mostly covered only one dimension, either subjective or objective. Fewer studies in the literature analyse the overall impact of ICT empirically. Researchers reveal a significant role of ICT in economic progress, but the aspect of wellbeing in the context of ICT is often ignored, especially in the case of its subjective nature, and researchers did not use multiple dimensions of ICT.

Currently, various metrics of wellbeing have been examined in the literature for the impact of technologies, but the impact of ICT on SWB has not been explored at the cross-country level. Previous studies have primarily relied on past surveys that capture only one dimension of

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happiness, such as positive feelings, but they tend to overlook the adverse impact. Several indices have been developed by international organizations to measure subjective wellbeing but have failed to capture progress over time. Therefore, this study aims to fill this gap by addressing both dimensions of wellbeing using a proxy for subjective wellbeing and considering multiple dimensions of ICT.

Empirical Framework

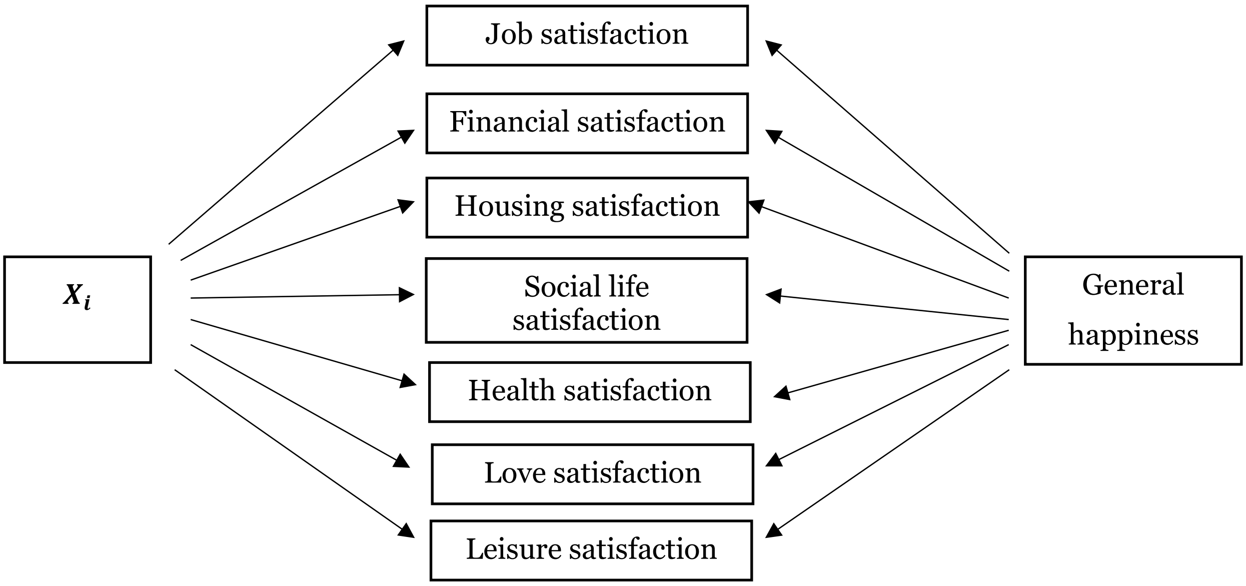

Figure 1. The nexus between observable factors and general happiness (Aldieri *et al.*, 2021)

In this section, we develop a theoretical framework that supports our empirical analysis. The various secondary analyses attempt to identify the factors that contribute to an increase or decrease in happiness, which econometricians refer to as explanatory variables. Various domains of life that are highlighted by Van Praag & Ferrer-i-Carbonell (2011) provide individuals with general happiness directly. When questions are asked to respondents about their life satisfaction, they go into a thought process as to "how satisfied I am with marriage, health, income, job, and social interaction". For overall evaluation, we have to sum the different dimensions of life with each other. In line with Van Praag & Ferrer-i-Carbonell (2011), SWB is chosen from the World Gallup Poll survey which includes different dimensions of life satisfaction. Figure 1 depicts the general happiness by observable factors X_i.

The utility function of individual j at time t is assumed to be the following:

$$U_{jt} = U\,(SWB_{jt}, SWB_{jt-1}, I_{jt}, \frac{I_{jt}}{I_t}, S_t, S_{t-1}) \tag{1}$$

The description of variables is as follows:

I_{jt}= Consumption of individual

$\frac{I_{jt}}{I_t}$=Average level of consumption of all individuals

S_t = Socioeconomic measures in developed countries at a time

SWB_{jt}= Subjective wellbeing indicator derived from satisfaction factors

Due to the pro-cycling behaviour of consumption and economic development measures, we can conjecture that:

$$I_{jt} = I_{jt}\ (ICT_t) \tag{2}$$

$$S_t = S_t\ (ICT_t) \tag{3}$$

where ICT is the impact of ICTs on socio-economic measures, so equation (1) can be converted as follows:

$$U_{jt} = U\ [SWB_{jt}, SWB_{jt-1}, I_{jt}\ (ICT_t\ ), I_{jt-1}(ICT_t), S_t(ICT_t),\ S_{t-1}(ICT_t)] \tag{4}$$

From the above equation, we can easily derive the following equation:

$$D.SWB_{jt} = f(D.SWB_{jt-1};\ \mathrm{D}.ICT_t;\ D.ICT_{t-1}) \tag{5}$$

The relationship in equation (5), where “D.” denotes change, we are going to test in the next section by using an econometric model.

Data and Methodology

Variables and data source

This study investigates panel data spanning 14 years, from 2006 to 2019, to analyse ICT as a determinant of happiness. This study includes 40 countries based on higher SWB; the list of countries is given in Appendix Table 1. Various international organizations, institutions, and scholars have presented different indicators measuring progress, development, and social wellbeing. Among the most famous indicators are the Human Development Index (HDI), the Genuine Progress Indicator (GPI), the Index of Sustainable Economic Welfare (ISEW), the Gross National Happiness (GNH), the Quality-of-Life Index, the Life Quality Index (LQI), and the Happy Planet Index (HPI), as well as the Economic Performance and Social Progress (OECD Index). We utilize world Gallup Poll survey data as a measure of subjective wellbeing. Variables are employed to construct indices with similar categorizations (D’Acci, 2011; Ganju *et al.*, 2016; Maiti *et al.*, 2020). This study examines the SWB of people at the cross-country level in five major areas: economic, institutional, human wellbeing, environmental, and ICT. Variables and data sources are provided in Table 2.

Construction of indices

Using the global min-max approach for the construction of indices, all the variables used here are first normalized, then combined, and given equal weights. There is no justification for not allocating equal weights, because a similar weighting approach is also used by the United Nations Development Programme (UNDP). Here, an effort is made to determine the elements that show the relationship among subjective wellbeing, human progress, environmental progress, governance, and economic wellbeing.

Economic Development: Economic development depends on a country's productivity and income, which, in turn, affects an individual's feelings and psychological wellbeing. A higher income enables a person to fulfil their desires in alignment with their preferences, fostering a happier attitude and a zest for life. This is why GDP per capita is used as a proxy. However, income distribution is not equal among people, leading to income inequality at the national level and heightened social tension. Consequently, social tension is determined by the Gini coefficient. Acemoglu & Restrepo (2018) argued that unemployment also contributes to social tension and inversely affects wellbeing. To combine these three variables reflecting economic development, a simple arithmetic average with equal weights is used.

Governance: The vital connection between happiness and government has been overlooked in the literature. Governments and institutions have a significant influence on individuals' lives. Therefore, the government effectiveness index, as taken by world governance indicators, is also included.

Human Progress: Health is the most prominent determinant of human wellbeing. People who lead healthier lives can move anywhere to enjoy their lives and feel better than those who are not physically or mentally fit. Life expectancy is considered a proxy for human wellbeing.

Environmental Progress: The environment is crucial for humans, and factors such as pollution, weather, and climate change can all impact how they feel. Environmental change also determines sustainable development, which increases individuals' satisfaction. The consumption of renewable resources as a percentage of total energy consumption is the most prominent indicator. Additionally, a large emission of CO_2 leads to a worse and suffocating environment. Greenery also attracts human beings and creates a friendly environment, and forest cover is used as a proxy for the environmental index. It is constructed using the same methodology as an economic development index.

Information and Communication Technology: Today, ICT plays an important role in reducing anxiety and loneliness through its applications. It also has the power to change one's mood and overall quality of life, expanding the social circles of human beings. It connects people who are geographically separated and can even inspire societal unrest through privacy and cyber risks. SWB is determined through a questionnaire conducted by the World Gallup Poll, covering all aspects of an individual's life. The objective of these questions is to assess an individual's psychological wellbeing in comparison to their peers and the historical and contemporary contexts. The impact of ICT on subjective wellbeing is discussed in previous sections and, now, an empirical investigation is required. Due to the lack of long-term data availability, the ICT index is associated with and prepared using four variables, as follows:

1. Mobile Cellular subscriptions (per 100 people);
2. Internet users (per 100 people);
3. Fixed broadband subscriptions (per 100 people);
4. Fixed telephone subscriptions (per 100 people).

First, these variables were used to construct the ICT index. Ganju *et al.* (2016) used the same variables, and Maiti *et al.* (2020) also employed them, albeit without fixed broadband subscriptions. Further, the ICT exposure index was developed using Principal Component Analysis, as detailed in the work by Hanafizadeh *et al.* (2009) on ICT index construction.

Evidently, there is a significant disparity in all ICT indicators across countries over time in the above literature. Mobile cellular subscriptions substantially increased in all countries. Mobile cellular subscriptions in the UAE reached their peak in 2016. Fixed telephone subscriptions began to decline due to the increasing prevalence of mobile cellular subscriptions over time. The groups of Internet users and fixed broadband subscriptions have also witnessed significant improvements. An integrated index was developed by combining all these variables after normalizing them with the global min-max method and assigning equal weights. The scale of the ICT index ranges from 0 to 1, with a higher value indicating greater ICT exposure. It is worth noting that Switzerland reached its peak in 2016. Remarkably, ICT exposure is on the rise in all the data sets of sample countries.

Econometric model

We create the following function to undertake empirical estimation of the relationship between the variables:

$$SWB = f\ (Governance, Human\ wellbeing, Economic\ development, Environment, ICTs)$$

Here, subjective wellbeing is measured by the happiness index (ladder wellbeing), which is a function of ICT measured by mobile cellular subscriptions, fixed telephone subscriptions, fixed broadband subscriptions and Internet users, and other variables like life expectancy at birth, effective governance, economic development and environmental indices, which are expected to be linked to SWB. To analyze the relationship between SWB and its explanatory variables, the given generalized panel ARDL (p, q,…, q) model according to Pesaran *et al.,* (1999) is constructed:

$$SWB_{it} = \sum_{j=i}^{p} \delta_{it}\, SWB_{it-1} + \sum_{j=0}^{q} \gamma_{ij}\, X_{it-j} + \mu_i + \varepsilon_{it} \quad (6)$$

where SWB_{it} indicates the dependent variable for group i and X_{it} $(K \times 1)$ is the vector of explanatory variables for group i, γ_{ij} are (k × 1) coefficient vectors, δ_{it} are the coefficients of the lagged dependent variables and scalars; groups are denoted by $i = 1, 2, \dots, 40$; time periods by $t = 2006 - 2019$; whereas μ_i represents the fixed effects and $\boldsymbol{\varepsilon_{it}}$ shows an error term. The following specified re-parameterized model in error correction form is convenient to work with to reduce heteroskedasticity and multicollinearity:

$$\Delta SWB_{it} = \theta_i\left(SWB_{it-1} + \beta'_i X_{it}\right) + \sum_{j=i}^{p-1} \delta_{ij}^* \Delta SWB_{it-j} + \sum_{j=i}^{p-1} \gamma'_{ij} \Delta X_{it-j} + \mu_i + \varepsilon_{it} \tag{7}$$

where $\quad \Delta SWB_{it} = (SWB_{it} - SWB_{it-j})$,

$$\theta_i = -\left(1 - \sum_{j=0}^{p} \delta_{ij}\right), \qquad \beta_i = \left(\sum_{j=0}^{q} \gamma_{ij}\right),$$

$$\delta_{ij}^* = -\left(\sum_{m=j+1}^{p} \delta_{m+1}\right), \qquad \gamma_{ij}^* = -\left(\sum_{m=j+1}^{q} \gamma_{m+1}\right).$$

This study uses Pesaran *et al.*, (1999) to construct an empirical model. The following Error Correction Model (ECM) is constructed based on variables using Equation (7).

$$\Delta SWB_{it} = \theta_i\left[SWB_{it-1} + \beta_{i,1} EG_{i,t-1} + \beta_{i,2} LEB_{i,t-1} + \beta_{i,3} EDI_{i,t-1} + \beta_{i,4} EI_{i,t-1} + \beta_{i,5} ICT_{i,t-1}\right] + \sum_{k=0}^{p-1} a_{ij}\, SWB_{it-j} + \sum_{k=0}^{p-1} b_{ij}\, EG_{it-k} + \sum_{k=0}^{p-1} c_{ij}\, LEB_{it-k} + \sum_{k=0}^{p-1} d_{ij}\, EDI_{it-k} + \sum_{k=0}^{p-1} e_{ij}\, EI_{it-k} + \sum_{k=0}^{p-1} f_{ij}\, ICT_{it-k} + + \mu_i + \varepsilon_{it} \tag{8}$$

where $i = 1, 2, \dots, 40$; time periods by $t = 2006 - 2019$. The variables SWB, EG, LEB, EDI, EI, and ICT represent subjective wellbeing, effective governance, life expectancy at birth, economic development index, environmental index, and information and communication technology exposure index, respectively. The $\beta_{i,1}$, $\beta_{i,2}$, $\beta_{i,3}$, $\beta_{i,4}$, and β_{i5} are the long-run coefficients; a_{ij}, b_{ij}, c_{ij}, d_{ij}, $e_{ij,}$ and f_{ij} are the short-run coefficients; $\mu_{\boldsymbol{i}}$ is the state effect; ε_{it} is the error term, and θ_i is the error correction term. As to the PMG technique and related theory of inference process, kindly refer to Pesaran *et al.* (1999).

Results and Discussions

To analyse the data, both descriptive and inferential techniques are used. The results of both techniques are included below with pertinent analysis.

Descriptive analysis

SWB is used as a dependent variable in these analyses. Independent variables are EG, LEB, EDI, EI, and ICT, respectively. A set of descriptive results are given in Table 3.

The mean value of SWB is 6.63, with an estimated standard deviation of 0.72 for all 40 countries over 14 years from 2006 to 2019. The minimum value of SWB was 4.38 for Serbia in

2009, representing the lowest SWB in the entire dataset, while the maximum value was 7.99 for Malta in 2006, indicating the highest SWB within it.

The mean values of the variables used in the ICT index are 120.61, 34.1, 67.979, and 23.43, with estimated standard deviations of 25.049, 14.7, 21.897, and 11.656 for mobile cellular subscriptions, fixed telephone subscriptions, Internet users, and fixed broadband subscriptions, respectively. The minimum values for mobile cellular subscriptions, fixed telephone subscriptions, Internet users, and fixed broadband subscriptions are 33.224, 4.862, 3.268, and 0.196 in the countries Costa Rica (2006), Finland (2019) and Kazakhstan (2006), respectively. The maximum values for mobile cellular subscriptions, fixed telephone subscriptions, Internet users, and fixed broadband subscriptions are 212.64, 67.33, 99.15, and 46.82 in the countries UAE (2016), Switzerland (2006), UAE (2019), and Switzerland (2019), respectively.

The mean values of the variables used in the Economic Development Index are 31,397.862, 7.164, and 35.150, with estimated standard deviations of 23,406.188, 3.795, and 7.652 for GDP per capita, the unemployment rate, and Gini, respectively. The minimum values of GDP per capita, the unemployment rate, and Gini are 3,261.76, 1.64, and 23.20 in the countries of El Salvador (2006), the UAE (2016), which showed the lowest unemployment, and the Slovak Republic (2017), respectively. The maximum values of GDP per capita, the unemployment rate, and Gini are 112,37, 26.09, and 55.60 in the countries of Luxembourg (2007), Spain (2013), and Brazil (2006), which has the lowest income inequality, respectively.

The mean value of effective governance is 1.022 with an estimated standard deviation of .74 for all 40 countries over 14 years from 2006 to 2019. The minimum value of effective governance for the whole data set is -.76 for Guatemala in 2012, which has the lowest effective governance, and the maximum value is 2.35 for Denmark in 2007, which has the highest effective governance. The mean value of life expectancy at birth is 78.518 with an estimated standard deviation of 3.522 for all 40 countries over 14 years from 2006 to 2019. The minimum value of life expectancy at birth for the whole data set was 66.15 for Kazakhstan in 2006, which has the lowest life expectancy rate at birth, and the maximum value is 83.75 for Switzerland in 2018, which has the highest life expectancy at birth.

The mean values of variables used in the environmental index are 7.633, 31.477, and 20.420 with estimated standard deviations of 4.918, 18.117, and 16.256 for carbon dioxide emissions metric tons per capita, forest area to land area, and renewable energy consumption to total energy consumption, respectively. The minimum values of carbon dioxide emissions in metric tons per capita, forest area to land area, and renewable energy consumption to total energy consumption are 0.803, 1.094, and 0.1018 in countries Guatemala (2010), Malta (2006) and UAE (2012), respectively. The maximum values of carbon dioxide emissions in metric tons per capita, forest area to land area, and renewable energy consumption to total energy consumption are 24.834, 73.736, and 67.442 in countries Luxembourg (2006), Finland (2015), and Guatemala (2012), respectively.

Inferential analysis

In inferential analysis, statistical estimation is done on the pre-defined econometric model in this study, which is explained previously, and econometric results are appended below.

Econometric results and panel data estimation

The sequence of tests listed below is given for an estimate of the panel dataset. In this section, we compare the Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE) estimation results.

Test for multi-collinearity

The primary concern of econometric analysis is to determine whether there is multicollinearity among the independent variables. To check for multicollinearity, we calculate the variance inflation factors (VIFs) for the independent variables. Table 4 displays the VIF results for investigating multicollinearity. The selected variables in the set indicate that there is no multicollinearity. According to Damodar Gujarati (2022), if the VIF value is less than 5, multicollinearity is not a problem. However, in general, it should not exceed 10.

Unit root test

Before examining the inferential relationships among the variables, it is essential to assess the time-series properties of these variables. This step ensures the accurate application of the panel ARDL method, which is appropriate for variables that are purely I(0) and I(1), but not for I(2) variables (Pesaran *et al.* 2001). The Im *et al.* (2003) panel unit root test was performed to check the stationarity properties of variables. The Im-Pesaran-Shin (IPS) unit-root test results show that LEB_{it} is stationary at level. Table 4, Panel (b) indicates that $SWB_{it}, EG_{it}, EDI_{it}, EI_{it}$, and ICT_{it} exhibit stationarity at the first difference, suggesting that they are I(1) variables based on the IPS panel unit root test.

Hausman test

The Hausman test is performed to select the best option between PMG and MG estimators and then also between PMG and DFE based on consistency and efficiency properties. The results are given in Table 5. PMG, MG, and DFE are compared having the null hypothesis for the final decision. The result shows that PMG is preferred, because the p-value is >0.05 and the null hypothesis is accepted. In this case, if we perform MG or DFE, it generates biased estimators.

Comparison of PMG, MG, and DFE with long-run and short-run estimations

The methodologies of PMG, MG, and DFE are used for estimating and presenting the results, which are shown in Table 5. Among these three, the PMG technique examines the final results. The benefit of using this technique is its ability to determine both long-run and short-run results, as well as long-run equilibrium. It exhibits low collinearity, greater efficiency, and a higher degree of freedom. PMG accounts for a lower degree of heterogeneity and assumes homogeneity in the long-run coefficients.

However, it allows for short-run coefficients and error variances in the presence of heterogeneity. This flexibility permits long-run homogeneity for groups and explanatory variables. The MG approach is highly sensitive to outliers, but PMG is less sensitive. Based on these arguments, the PMG technique is considered the best for investigating the relationship between SWB and regressors in dynamic heterogeneous panel models. The results show that ICT diffusion, life expectancy at birth, economic development, and effective governance have statistically significant relationships with SWB in the long run with PMG estimation, but all regressors are insignificant except for effective governance in the DFE long-run model.

ICT_{it} affects subjective wellbeing (SWB_{it}) positively in the long run at a 1% significance level, as well as in the short run at a 10% significance level, and it is significant in the case of PMG. Social innovations increase ICT exposure day by day and influence various domains of life. Thus, ICT diffusion and exposure increase the happiness margin for the people in sample countries and the need to explore more forums of ICT. The reasons behind the positive relationship between ICT_{it} and SWB_{it} include connectivity, access to information, the ability to work remotely to improve living standards, and opportunities for entertainment and leisure.

The short-run results also affirm this. The reason is that those people who did not have ICT goods before experience a change in their standard of living as they gain access to the new ICT technology and goods. Consequently, ICT increases the happiness of people living in sample countries. To delve deeper, a 1% increase in ICT diffusion results in a SWB upsurge of around 125% in the long run and 255% in the short run. These results are consistent with previous studies (Castellacci & Tveito, 2016; Castellacci & Viñas-Bardolet, 2019; Ganju *et al.*, 2016; Maiti *et al.*, 2020; Rotondi *et al.*, 2017; Sabatini & Sarracino, 2017). Short-run results in Table 5 show that the error correction term(θ_i) is significant at a 1% level, but all variables in the three models are insignificant, except ICT_{it} and LEB_{it} at 10% and 5% level, respectively.

Estimations show that the environmental index (EI_{it}) is insignificant in both the short run and the long run. The reason is that all countries are capitalistic and do not focus on an environmental situation that has a very high opportunity cost for human beings (O'Mahony, 2021). It also includes individual differences, cultural factors, and the specific aspects of the environment being considered (Diener *et al.*, 2009).

The slope coefficient of effective governance (EG_{it}) is negative, which means that effective governance restrains the happiness of individuals living in the sample countries. There are two types of arguments in the case of effective governance. First, the people in developed and higher SWB countries do not like government intervention. As the government becomes more effective, there will also be an upsurge in government intervention. This will decrease freedom and personal opinion, which is consistent with this study. Consequently, happiness decreases as effective governance rises. The contrary argument is that, as effective governance increases, it leads to higher GDP and societal welfare. Ultimately, it will lead to increased happiness (Cárcaba *et al.*, 2022; Helliwell & Putnam, 2004).

The most interesting aspect of the estimation is life expectancy at birth (LEB_{it}), which exerts a positive impact on SWB_{it} in the long run but harms SWB_{it} in the short run. The reason is an individual's expectation about their life when thinking about it in the long run. It will increase SWB_{it}, but life expectancy at birth has negative results in the short run due to short-term shocks, such as calamities, epidemics, and natural disasters.

Economic development (EDI_{it}) also has a positive impact on happiness. Income is the subject of debate due to the happiness paradox (Easterlin *et al.*, 2010; Stevenson & Wolfers, 2008). GDP yields positive results in this research due to high-income countries and also highlights the issue of inequality and the unemployment rate. However, economic development is insignificant in the short run. These results are consistent with previous studies (Delhey & Dragolov, 2014; Layte, 2012; Oishi *et al.*, 2011).

Conclusion and Policy Implications

The empirical relationship between happiness and ICT has not been explored extensively yet, but our research contributes to the literature. ICT diffusion is very complicated, both in terms of its spread and depth, due to its ubiquity. We demonstrate the positive impact of ICT on SWB resulting from an increase in mobile phone subscriptions, fixed broadband subscriptions, telephone subscriptions, and Internet use. Moreover, we also show the impact of effective governance on SWB, which follows an inverse direction due to an increase in government interventions. Estimates indicate that the environmental index has a negligible impact in both the short and long term due to the universal adoption of capitalism across all countries. This results from the prioritization of economic opportunities over environmental concerns, as highlighted by O'Mahony (2021).

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On the other hand, SWB is positively affected by economic development and human progress, as evidenced by an increase in GDP per capita and life expectancy at birth. We anticipate that the information systems research community will be able to gather an appropriate set of ICT knowledge to examine these issues.

The policy implications of the study, in line with the estimated results, are as follows: the results of this study are very beneficial to policymakers because they provide information on ICT diffusion leading to wellbeing. Therefore, policymakers should formulate policies that promote wellbeing instead of adopting a traditional approach. The governments of the sample countries should make decisions and rules that enhance the happiness of individuals through government effectiveness and minimal intervention in their lives. Sample countries should focus more on the health sector for human progress, because it increases individual happiness.

Research Implications

Since ancient Greek philosophy, the concept of wellbeing has been complex and has evolved in each era due to differences in the domains of life that are subject to change in the future, as discussed by philosophers, such as Aristotle, Plato, Socrates, and Kahneman *et al.* (1999). Because of this ambiguity, ICT could potentially play a significant role in research on information and wellbeing. This research explores the positive impact of ICT diffusion on subjective SWB. It is important to note that, in this study, the impact of ICT diffusion is found to be positive, but there is also the possibility of a negative effect on society. For instance, one argument is that ICT may lead to an increase in unemployment due to a reduced demand for unskilled workers. Additionally, it could contribute to increased wage inequality (Acemoglu & Restrepo, 2018). Moreover, it posits a negative effect stemming from differences in ICT diffusion.

Limitations and Suggestions for Future Research

ICT diffusion shows a direct relationship with subjective wellbeing but some limitations still exist. First, there may be some omitted variables that drive the results. Unobserved variables may be included in the research. In this study, we used the PMG (ARDL) technique, but the researcher can use additional econometric specifications, such as a slope homogeneity test and a cross-sectional dependence test. Second, we use only four dimensions of ICT, namely mobile cellular subscriptions, fixed broadband subscriptions, Internet use, and telephone subscriptions. But our ICT index does not include other dimensions of ICT, such as secure Internet servers. Future researchers could include the other dimensions of ICT in this innovative world.

The other limitation is that the majority of countries in the sample are European. Europe's population constitutes less than 10% of the global population. We suggest that future researchers would increase the sample size based on population. We hope that this evidence of ICT as a determinant of happiness will pave the way for future researchers to show how ICT enhances the subjective wellbeing of people across countries. This study analyses the cross-country effects of ICT diffusion on SWB; a similar individual-level analysis is also possible.

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Appendix

Table 1. List of Sample Countries

Sr.	Country	Sr.	Country	Sr.	Country	Sr.	Country
1	Australia	11	Estonia	21	Malta	31	United Arab Emirates
2	Austria	12	Finland	22	Mexico	32	United Kingdom
3	Belgium	13	France	23	Netherlands	33	United States
4	Brazil	14	Germany	24	Norway	34	Uruguay
5	Canada	15	Guatemala	25	Panama	35	El Salvador
6	Chile	16	Ireland	26	Slovak Republic	36	Kazakhstan
7	Costa Rica	17	Israel	27	Slovenia	37	Poland
8	Cyprus	18	Italy	28	Spain	38	Romania
9	Czech Republic	19	Lithuania	29	Sweden	39	Serbia
10	Denmark	20	Luxembourg	30	Switzerland	40	Mauritius

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Table 2. Measures and Indicators

Variable	Definition	Indicators/Scale/Source
EDI	Economic Development Index	GDP per Capita Unemployment rate Gini coefficient Source: World Development Indicators (WDI)
ICT	Information communication and technology exposure index	Mobile Cellular subscriptions (per 100 people) Internet users (per 100 people) Fixed broadband subscriptions (per 100 people) Fixed telephone subscriptions (per 100 people) Source: World Development Indicators (WDI)
EI	Environmental Index	a) Carbon dioxide emissions in metric tons per capita b) Forest Area to Land Area c) Renewable energy consumption to total energy consumption Source: World Development Indicators (WDI)
EG	Effective Governance	Scale: -2.5 to 2.5 (weak – strong) governance Source: The Worldwide Governance Indicators (WGI)
LEB	Life expectancy at birth, years	Source: World Development Indicators (WDI)
SWB	Subjective Wellbeing	Source: Gallup World Poll, shared in World Happiness Report (2021). Scale: 1–10

Table 3. Descriptive Statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Effective Governance	560	1.022	.74	-.76	2.35
GDP per capita	560	31397.862	23406.188	3261.764	112373
Unemployment rate	560	7.164	3.795	1.64	26.09
Gini	560	35.15	7.652	23.2	55.6
Life expectancy at birth	560	78.518	3.522	66.15	83.754
CO2 emissions metric tons per capita	560	7.633	4.918	.803	24.834
Forest area to land area	560	31.477	18.117	1.094	73.736
Renewable energy consumption	560	20.42	16.256	.102	67.442
Mobile cellular telephone subscription	560	120.61	25.049	33.224	212.639
Fixed telephone subscription	560	34.1	14.7	4.862	67.334
Internet users %	560	67.979	21.897	3.268	99.15
Fixed broadband subscription	560	23.43	11.656	.196	46.82
Subjective wellbeing	560	6.625	.7206	4.38	7.989

Table 4. Diagnostic Tests

Panel (a): Investigating multicollinearity			Panel (b): Im-Pesaran-Shin unit-root test stationary Test (IPS)		
Variables	VIF	$1/VIF$	Statistics W-t-Bar		
EG_{it}	3.762	.266	Variables	At level	At first level
LEB_{it}	3.353	.298	SWB_{it}	-1.1438	-9.1378***
EDI_{it}	3.171	.315	EG_{it}	-1.2597	-7.2594***
EI_{it}	2.034	.492	LEB_{it}	-4.6447***	---
ICT_{it}	1.126	.888	EDI_{it}	-0.1436	-5.9349***
Mean VIF	2.689	-	EI_{it}	1.9502	-6.5082***
			ICT_{it}	0.9118	-8.6319***
*** shows the level of 1% statistical significance.					

Table 5. A Comparison of MG, DFE, and PMG

	Coefficients		
	MG	**DFE**	**PMG**
	Long Run Parameters		
$\boldsymbol{EG_{it}}$	2.145 (1.664)	.4654*** (0.196)	-.4139*** (.117)
$\boldsymbol{LEB_{it}}$	22.421 (1.664)	0.614 (0.728)	1.0501*** (.468)
$\boldsymbol{EDI_{it}}$	-7.141 (17.750)	-0.552 (0.590)	2.392*** (.352)
$\boldsymbol{EI_{it}}$	-10.392 (36.875)	0.781 (0.679)	.1503 (.3705)
$\boldsymbol{ICT_{it}}$	-31.725 (19.612)	0.008 (0.394)	1.256*** (.2484)
	Average Convergence Parameter		
$\boldsymbol{\theta_i}$	-1.165*** (0.306)	-0.495*** (0.040)	-.497*** (.0724)
	Short Run Parameters		
$\boldsymbol{\Delta EG_{it}}$	-0.188 (1.171)	-0.065 (0.132)	.0936 (.1817)
$\boldsymbol{\Delta LEB_{it}}$	-408.935 (403.750)	-1.260 (0.851)	-42.431** (20.3001)
$\boldsymbol{\Delta EDI_{it}}$	22740.260 (67157.680)	-0.064 (0.447)	-13234.58 (15305.41)
$\boldsymbol{\Delta EI_{it}}$	13.526 (18.469)	-0.439 (0.583)	-18.107 (16.7115)
$\boldsymbol{\Delta ICT_{it}}$	15.530 (19.867)	0.572 (0.484)	2.551* (1.4485)
C	25.215 (1956.978)	2.824*** (0.364)	-558.429 (610.105)
(Hausman)$_{\mathbf{PMG/MG}}$		**(Hausman)$_{\mathbf{PMG/MG}}$**	
H_0: PMG H_1: DFE	$\chi^2(5)$ = -154.15	H_0: PMG H_1: DFE	$\chi^2(5)$ = 0.02
Prob.>χ^2=0.7342		Prob.>χ^2= 01.000	
Remarks		**PMG is efficient & consistent**	
Note: Standard errors of parameters are given in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%. θ_i is the error correction term			

Unveiling Business Activity Patterns of Digital Transformation through K-Means Clustering with Universal Sentence Encoder in Transport and Logistics Sectors

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Abstract: Digital transformation brings several key benefits to transportation and logistics firms, such as operational efficiency, improved customer experience, and supply chain visibility. This study seeks to identify and categorize business activities within the transportation and logistics sector, focusing on themes related to digital transformation. Additionally, it analyses the impact of firm size and sales performance. Data were sourced from 24 annual reports of four firms listed in the SET, covering the study period of 2017-2022. The study used context-free grammar-based verb patterns and a custom-made dictionary to extract business activities. The study used the Universal Sentence Encoder to represent the text and relied on the Dunn-Index and Silhouette score to determine the optimal number of clusters (both 8 clusters). Subsequently, K-means clustering was performed using these 8 clusters, leading to the categorization of eight digital transformation themes. Among these themes, profit management and regulation compliance are interesting discoveries, as they are rarely mentioned in previous studies. A total of 104 business activities were extracted as a result. The study also found that Online-to-Offline activity is an effective method for business model innovation, as well as a contemporary marketing tool.

Keywords: digital transformation, business activities, k-mean, logistics, Universal Sentence Encoder

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Introduction

Nearly every industry, including transportation and logistics, has witnessed significant changes in business operations due to the proliferation of digital technology. Incumbent firms must now embrace digital transformation to enhance operations, customer relationships, and business models (Kraus *et al.*, 2022). For example, maritime companies focus on cybersecurity to meet international regulations (Kechagias *et al.*, 2022), while shipping firms adopt blockchain technology for customs practices (Othman *et al.*, 2022). Logistics and transportation are also the key components in the operations of most firms across industries. Hence, digital transformation in these sectors plays a crucial role in transitioning the entire economy to Industry 4.0 (Varol *et al.*, 2022).

Similar to many industries, this sector encounters challenges in its digital transformation journey, primarily due to complexity. It encompasses diverse participants, including intermediaries, end-customers, warehouse operators, terminal operators, and others, contributing to a lag in digital adoption (Cichosz *et al.*, 2020). Additionally, there is a lack of awareness, effective strategies, and initiatives for successful digital transformation (Tijan *et al.*, 2021). Also, firms often rely on ad-hoc practices due to a shortage of comprehensive guidelines (Sun *et al.*, 2021).

Among academics as well as practitioners, the Digital Maturity Model (DMM) is currently accepted as a tool for navigating firms through digital transformation (Gökalp & Martinez, 2022). The DMM comprises two components: dimensions, representing essential tasks; and stages, reflecting different levels of maturity, from basic digital adoption to advanced (Ryan *et al.*, 2020). The model is commonly used to assess an organization's current level of digital maturity and provide guidance on how to progress through various stages of transformation (Haryanti *et al.*, 2023).

While numerous digital maturity models have been proposed, the majority of them still offer an incomplete picture of digital maturity (Teichert, 2019). This ambiguity is evident in the observation that most models in the literature lack coverage of all dimensions of digitalization (Hellweg *et al.*, 2021), have varying numbers of dimensions (Thordsen *et al.*, 2020), and evaluate areas that have not been empirically verified (Tubis, 2023), among other factors. In addition, the majority of models seldom include detailed low-level concepts, such as indicators (Bley *et al.*, 2020), in an effort to minimize abstraction and enhance clarity.

A sector-specific Digital Maturity Model, designed for the transportation and logistics sector to address its unique needs, is still in its early stages. This aligns with evidence indicating the underdevelopment of maturity models in the service industry (Teichert, 2019), whereas certain papers concentrate on models tailored for specific transportation modes or sub-

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sectors, such as shipping (Rakoma, 2021) or airline services (Kıyıklık *et al.*, 2022). In this study, we employ automated phrase extraction to answer these research questions: 1) What are the empirical dimensions essential for digital transformation in this sector? 2) What are the corresponding business activities of those obtained dimensions? The study fills a literature gap by proposing an alternative approach to identify critical elements for sector transformation. Additionally, examining the problem at the activities level enhances understanding of the real practices of digital transformation. Our study also explores the pandemic's impact on the sector's digital transformation as it was shaped and accelerated by the crisis (Zimnoch, 2021).

This article is structured as follows. In the next section, we provide a comprehensive summary of the key literature relevant to our study. Following this, we delve into the research methodology, presenting a detailed account of our approach. Subsequently, the results are presented, setting the stage for a comprehensive discussion. Finally, we conclude with a synthesis of our findings, offering insights and implications derived from our study.

Literature Review

Digital transformation entails leveraging digital technologies to enhance various aspects of business, including business models, products, processes, and organizational structures (Verhoef *et al.*, 2021). In the transportation and logistics sector, digital transformation drivers vary from business to business. In the airline business, the high fixed-costs nature emphasizes the significance of minor cost reductions, such as ticket issuance, distribution, processing, and reconciliation, in improving airline companies' profitability (Heiets, 2022). In the maritime transport industry, investments in technology and collaborative technical cooperation among involved organizations are essential to meet stringent regulatory requirements (Tijan *et al.*, 2021).

Digital transformation in the sector is primarily characterized by employing digital technologies to significantly enhance efficiency. For example, blockchain is used for shipping documents to optimize transaction efficiency (Alahmadi *et al.*, 2022), and Internet of Things (IoT) data is harnessed to guide warehousing operations, thereby improving work efficiency (Liu & Ma, 2022). Using digital technology to create new value sources also holds high potential. While ridesharing is a popular digital business model for transportation startups (Remane *et al.*, 2017), incumbent firms may position themselves as Mobility as a Service (MaaS) providers, offering integrated transportation services, intermodal journey planning, bundled services, and multiple payment options (Alyavina *et al.*, 2022).

Digital transformation necessitates profound changes in firms' business activities. Business activities encompass all the economic endeavours undertaken by a company, with its primary aim being the generation of profit (Tuovila, 2022). In the value chain framework, business activities are the core components that enhance the value of resources and appeal to users. This concept involves a sequence of steps taken to transform an initial idea into a final product ready for delivery to consumers. The value chain comprises four supporting activities and five primary activities (Ricciotti, 2020).

In this age of rapid digital technology advancement, it is crucial to recognize that certain business activities have greatly improved. In logistics companies, for instance, IoT sensors are used to identify defective equipment suppliers, weaknesses in equipment, predict breakdowns, schedule repairs, and provide highly accurate long-term planning. These measures help firms improve maintenance activities and extend equipment lifespan (Ilyashenko *et al.*, 2020). Other generally observed changes in firms' business activities included co-creation with customers (Erevelles *et al.*, 2022), establishing new digital units (Bellantuono *et al.*, 2021), and incubating startups (Steiber & Alänge, 2020).

Unlike industries such as media, telecom, banking, and retail, the transportation and logistics sector, notably the shipping industry, has traditionally lagged in digital adoption. This can be attributed to its network-centric structure and the prevalence of family-controlled enterprises (Cichosz *et al.*, 2020; Raza *et al.*, 2023). The sector also deals with a lack of general guidelines, as its practices tend to be ad-hoc in nature (Sun *et al.*, 2021). Currently, the Digital Maturity Model (DMM) is accepted as a tool to guide firms in digital transformation. The model serves as an indicator of a company's maturity level or key stages in specific dimensions toward achieving digital transformation. It also acts as a reference point to guide firms' improvement efforts (Zapata *et al.*, 2020).

While many models for assessing digital maturity have been put forward, most of them provide only a partial view of the overall digital maturity landscape (Teichert, 2019) or rarely include detailed low-level concepts, such as indicators (Bley *et al.*, 2020), to reduce complexity and improve clarity. Furthermore, many models intended for the transportation and logistics sector are customized for specific transportation modes or sub-sectors, such as shipping (Rakoma, 2021) and airline services (Kıyıklık *et al.*, 2022). An example of such models is the maturity model for smart ports proposed by Boullauazan et al. (2023), which comprises five phases: silo, integration, supply-chain, port-wide, and inter-port. It encompasses five dimensions: port operations, synchromodality, safety and security, energy and environment, and capability.

Although obtaining a practical digital maturity model is challenging, particularly due to limited research information accessibility in some sub-sectors (Rakoma, 2021), Signal Theory suggests that valuable insights can be gleaned from a firm's voluntary disclosures. Companies often enhance and increase their information disclosure to signal their future prospects to investors, facilitating more efficient capital attraction at reduced costs (Salvi *et al.*, 2021). However, manually extracting digital transformation guidelines can be challenging due to the overwhelming volume of textual data. Additionally, some studies that use annual reports to investigate firms' digital transformation lack practical guidelines, relying solely on counting relevant key terms as observed in Eremina et al. (2019), Guo & Xu (2021) and Salvi et al. (2021).

With advancements in natural language processing and text analytics techniques, obtaining practical digital maturity models from firms' annual reports has become feasible. Information extraction techniques have been proven effective in uncovering hidden insights within economic texts, such as business news, company disclosures, and social media (Hobbs & Riloff, 2010). An available technique is automated key phrase extraction based on parts of speech (POS) tags. The technique relies on POS tags, which are labels assigned to words in a sentence based on their grammatical roles (e.g., noun, verb, adjective). By analyzing the POS tags, the system can identify and extract important phrases or terms from the text automatically (Sarkar, 2016). Modern natural language processing (NLP) algorithms can now easily identify word types in text, simplifying information extraction (Kochmar, 2022).

Automated key phrase extraction can be used for exploring insights from business texts. For example, non-domain-expert software project developers may use this method to acquire relevant business concepts before starting a project (Ménard & Ratté, 2016). The approach is also useful for opinion extraction about products from customer reviews (Htay & Lynn, 2013). Additionally, key phrase extraction is found effective in extracting verb patterns that are then interpreted as business activities relating to digital transformation (Promsa-ad & Kittiphattanabawon, 2023).

To derive empirical dimensions of digital maturity models and their corresponding business activities from firms' annual reports, one can start by extracting verb phrases, which can then be filtered to identify relevant business activities. These obtained business activities can then be grouped into themes or dimensions using clustering techniques. One such technique is K-means clustering, which aims to identify tightly-knit groups by minimizing the mean sum-of-squares deviation of each observation from its group's multivariate centre or centroid (Schwarz *et al.*, 2020). To conduct K-means clustering, we need to specify the desired number of clusters, 'k'. Subsequently, the K-means algorithm assigns each observation to one of these 'k' clusters (James *et al.*, 2023). For optimal clustering results, it is essential to assess them using cluster validity indices. Examples include the Dunn Index (DI), an internal measure quantifying cluster compactness and separation. Higher Dunn Index values indicate better clustering. Another such index is the Silhouette score, which evaluates cluster membership by

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comparing distances within and between clusters. A Silhouette value closer to one indicates better clustering (Ncir *et al.*, 2021).

To perform K-means clustering on unstructured data, like text, it is essential to first preprocess the data. This involves steps such as tokenization, stop-word removal, and converting the text into a numerical format. Numerical representation, typically achieved through methods like TF-IDF or word embeddings, is necessary for the application of mathematical and statistical techniques, including K-means clustering (Antons *et al.*, 2020). The Universal Sentence Encoder is one widely used text representation method that encodes sentences or phrases into 512-dimensional embedding vectors. It produces embeddings that represent the semantic content of text, making them suitable for various natural language processing tasks (Cer *et al.*, 2018).

Research Objectives

Our motivation is to discover empirical dimensions crucial for digital transformation in the transportation and logistics sector and to identify corresponding business activities associated with these dimensions. Our objectives are as follows:

1. To extract business activities relevant to digital transformation. This objective aims to reduce the abstraction of digital transformation by providing low-level evidence through business activities.
2. To cluster the obtained business activities into digital transformation themes. These themes will then be translated into dimensions of a digital maturity model.
3. To investigate whether firms' size and sales performance influenced their digital transformation during the pandemic.

Research Methodology

The methodology employed in this study aimed to obtain dimensions of a digital maturity model and their corresponding business activities. This section provides an overview of the methods used in the study, including data preparation techniques, verb phrase extraction, and clustering methodologies, outlined in Figure 1. Each process is detailed below.

1. Document Preparation

The study employed data from sampled firms' annual reports, which we converted from PDF to text format. Samples were selected from a population consisting of 34 firms from the transportation and logistics sector of the Stock Exchange of Thailand (SET). We excluded real-estate investment trusts (REITs) due to their unique characteristics, including a legal obligation to pay dividends. To be included in the sample, firms had to consistently publish annual reports from 2017 to 2022. Thirteen out of 32 firms met this criterion.

We calculated each firm's compound annual growth rate (CAGR) of revenue for both the pre-pandemic period (2017-2019) and the pandemic period (2020-2022). Firms were then ranked based on the percentage change in CAGR between these two periods. Additionally, firms were categorized by size, with those listed in the SET 50 or SET 100 considered large companies, and the rest as small or medium-sized. We selected two firms with the highest percentage change in CAGR, one from the large companies and one from the small and medium-sized firms, and two firms with the lowest percentage change in CAGR, maintaining size considerations.

In total, four firms were chosen for the sample. Therefore, 24 annual reports were used in this study. Firms typically emphasize their digital transformation practices in sections related to their business and market competition, so we focused on extracting text from those sections.

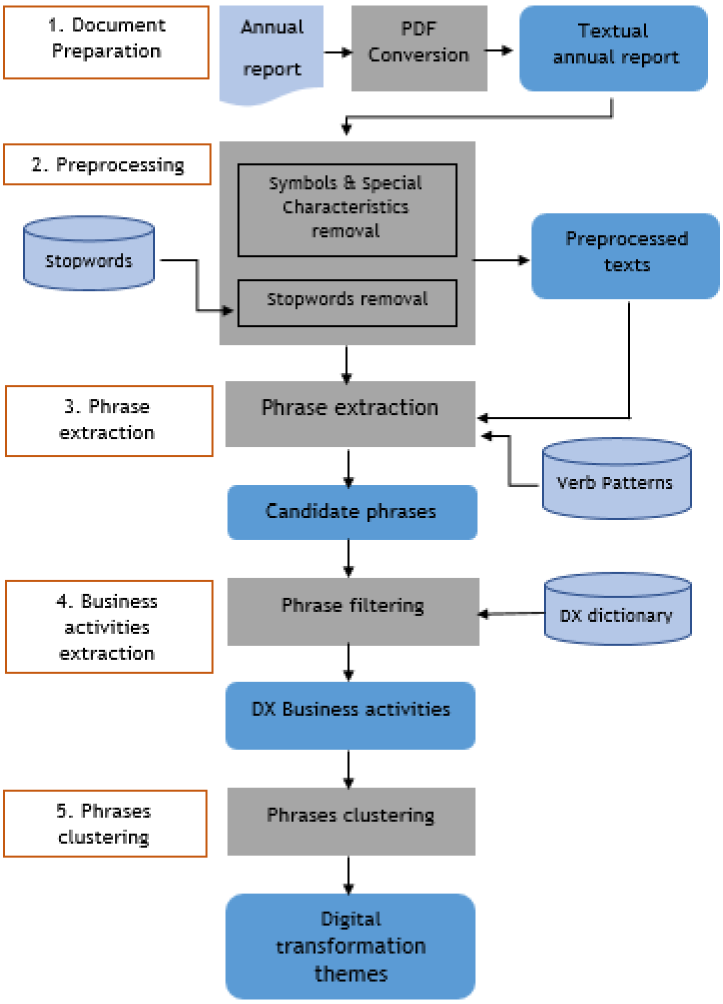

Figure 1. Proposed research processes

2. Preprocessing

The focus of this stage is to clean the text data and make it ready for further analysis. We removed stop-words, especially articles, and symbols like parentheses, to better align the text with specified verb patterns. Stop-words are common words in any language that occur frequently but provide little significant information about a phrase's meaning (Anandarajan *et al.*, 2019).

3. Phrase Extraction

This study utilized automated key phrase extraction relying on parts of speech (POS) tags, selected for its widespread use (Alami Merrouni *et al.*, 2020) and efficacy in identifying and extracting crucial phrases (Sarkar, 2016). The study used a Python syntax library to detect parts of speech in the text and extract relevant verb phrases that represent business activities, guided by English context-free grammar. The extraction process was primarily based on specified context-free grammar verb patterns derived from Jurafsky & Martin (2008) and supplemented with patterns from Swan (2016) and Carter & McCarthy (2006). These verb patterns can be classified into four groups: intransitive verb phrases, transitive verb phrases with a single object, transitive verb phrases with two objects, and transitive verb phrases with a single object and an object complement.

4. Business Activities Extraction

To obtain phrases relevant to business activities of digital transformation, the candidate phrases obtained from the previous stage were filtered by a custom-made dictionary. We constructed a digital transformation dictionary to filter extracted phrases, as our desired outputs were digital transformation-related business activities. The dictionary consisted of key terms derived from relevant sources covering words or phrases that could reflect digital transformation in transportation and logistics sectors. We also included key terms from the e-commerce and digital media sectors to align with the firm's business nature in the sample. The data sources and their word counts are presented in Table 1.

Phrases with specified keywords were translated into business activities. Some were edited for clarity, such as changing "analyzing data based on members" to "analyze data based on members".

5. Phrases Clustering

The acquired business activities were encoded using the Universal Sentence Encoder to create numerical representations (Fattoh *et al.*, 2022), facilitating further clustering analysis. Finally, we performed K-means clustering. Clustering is a method of grouping texts based on their textual features without any labelled variable guiding the process. Because no instruction is offered to the learning problem, it is often referred to as unsupervised learning (Debao *et al.*, 2021). Therefore, the method facilitates the translation of business activities into themes or dimensions. To identify the optimal *k* in K-means clustering, this study employed the Dunn-index metric and Silhouette score, as suggested in Gupta & Panda (2019) and Naeem & Wumaier (2018).

Table 1. List of sources used for constructing dictionary of digital transformation

Source	**Number of Key Terms**
The Effects of Digital Transformation on Firm Performance: Evidence from China's Manufacturing Sector (Guo & Xu, 2021)	49
Impact of the Digital Transformation of Small- and Medium-Sized Listed Companies on Performance: Based on a Cost-Benefit Analysis Framework (Teng *et al.*, 2022)	21
Digital Maturity and Corporate Performance: The Case of the Baltic States (Eremina *et al.*, 2019)	49
Gartner Glossary (Gartner, n.d.)	2,394
A Comprehensive E-Commerce Glossary (Contentor, n.d.)	172
Digital Media Glossary (Mediacrossing, n.d.)	59
Glossary for Digital Logistics & Transportation Management (Alpega Group, n.d.-a)	34
A Brief Glossary of E-commerce Logistics Lingo (OGOship, n.d.)	43
Digitalized Public Transport Glossary: Common Terms & Abbreviations (Tronteq, 2021)	12
Glossary of Important Emerging Transportation Technology Terms (Michigan Law, n.d.)	48
The Transit Technology Glossary (Via, 2021)	65
Telematics Glossary (TIS, n.d.)	157
Airport digital transformation:From operational performance to strategic opportunity (Amadeus, n.d.)	10
Glossary for Digital Logistics & Transportation Management (Alpega Group, n.d.-b)	74
Total	**3,187**

Results

Business activities extraction

Throughout the study period, all sampled firms were engaged in business activities related to digital transformation. A total of 104 unique business activities were extracted. Individually, the firms performed the following number of business activities, ranked from largest to smallest: 38, 30, 18, and 18. All business activities are illustrated in Figure 2.

Table 2 illustrates the impact of firm size and sales performance during the pandemic on a firm's digital transformation, measured by its focus on relevant business activities. The first row of the table categorizes firms by size, considering those listed in the SET 50 or SET 100 as large companies, and the rest as small or medium-sized. The left column of the table groups firms based on the percentage change in their compound annual growth rate (CAGR) before and during the pandemic. The numbers shown in the table were the number of relevant business activities performed by firms with the specified characteristics. Overall, no clear patterns emerged regarding the relationship between firm size, sales performance, and firm business activities during the pandemic. However, two firms serving retail customers exhibited a greater number of activities.

Figure 2.Extracted business activities during 2017–2022

Table 2. Influence of firm size and CAGR on firm digital transformation during the pandemic

Category of firm	Listed in SET 50/SET 100 index	Not listed in SET 50/SET 100 index
Negative percentage change in CAGR	38	18
Positive percentage change in CAGR	18	30

Digital transformation themes

We conducted K-means clustering using embeddings of the obtained business activities encoded with the Universal Sentence Encoder. Before performing K-means clustering, we used the Dunn Index and Silhouette score to identify the appropriate *k*. The higher Dunn Index values indicate better clustering results. From Table 3, the maximum Dunn Index was 0.370, suggesting an optimal number of clusters (*k*) of 8. The analysis of Silhouette score provided the same resultm as shown in Figure 3.

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Table 3. The optimal number of clusters based on Dunn-Index was 8

Number of K	Dunn-Index
2	0.267
3	0.299
4	0.301
5	0.347
6	0.321
7	0.335
8	**0.370**
9	0.365
10	0.350

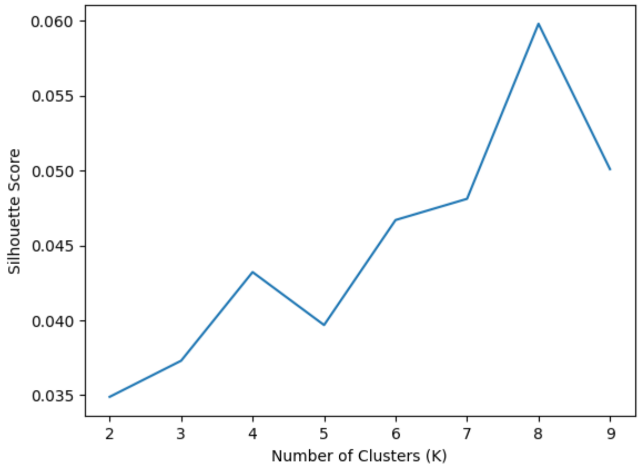

Figure 3. Silhouette score indicated the optimal k at 8

Performing K-means clustering with k=8 yielded the results presented in Table 4. The 'Themes' column represents clusters identified as critical dimensions for digital transformation, labelled based on characteristics of assigned business activities. The 'Example of Business Activities' column provides specific examples of relevant business activities for each theme. The categories and their corresponding number of activities were as follows: profit management (23), business model innovation (21), data analytics (18), security and cybersecurity (15), reach expansion (9), regulation compliance (9), technology investments (5), and digitization & digitalization (4).

From Table 4, examples of business activities could be considered as low-level concepts or indicators reflecting dimensions essential for digital transformation, representing more abstract concepts with less clarity. It also indicates the actions required for specific dimensions, which could be used as transformation guidelines. For instance, to address the element of security and cybersecurity in the transformation, one needs to focus on making strategic decisions about sourcing security training programs, training security officers, managing cybersecurity issues, etc.

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Table 4.Themes of digital transformation and their relevant business activities

	Theme	Examples of Business Activities
1	Business model innovation	target advertising activation, integrate online-offline media inventories, connect offline-online worlds, move towards digital commerce, switch to online channels, shift to online backup
2	Security & cybersecurity	produce cybersecurity management, designate appropriate security officers, train security personnel, outsource aviation trained security, improve security of ships
3	Regulation compliance	certify for compliance with ISO, monitor compliance, ensure data confidentiality, demonstrate compliance with AFS
4	Digitization & digitalization	send electronic invoices, accommodate digital payments, manage digital document, automate ticketing
5	Data analytics	interpret large amounts of data, combine real purchase data, analyze data based on members, build strong data scientist, incorporate artificial intelligence solutions
6	Reach expansion	reach broader customer network, maximize revenue on network, operate own network spanning transit, expand payment network of Rabbit Group
7	Technology investments	adopt technology in services, employ new technology, establish technology, bring in new technology, develop software
8	Profit management	adjust frequency capacity, maximize revenue per flight, project passenger cargo load factors, exercise tax exemption, handle premium cargo

Conclusions/Recommendations

While there is a growing literature on digital technology adoption in transportation and logistics, systematic guidelines are lacking due to the practices being considered ad-hoc. The Digital Maturity Model, commonly used to guide firms through digital transformation, is still in its infancy, offering an incomplete picture of the digital journey, particularly those tailored for the transportation and logistics sector. This study employed automated phrase extraction and clustering to identify empirical dimensions essential for digital transformation and their corresponding business activities in selected firms listed on the transportation and logistics sector of the Stock Exchange of Thailand. The study also explored the pandemic's impact on the sector's digital transformation.

Business activities were extracted by identifying verb phrases using verb patterns derived from English context-free grammar and filtering the obtained phrases using a custom-made dictionary. In total, 24 verb patterns and 3,044 key terms were used in the study. The themes were obtained using the K-means clustering technique based on phrase embeddings generated by the Universal Sentence Encoder. The clustering results were evaluated using the Dunn-Index metric and Silhouette Score. Both evaluation methods provided a similar optimal result of k=8.

The findings revealed that all sampled firms participated in business activities related to digital transformation throughout the study period. Each firm performed the following number of business activities, ranked from largest to smallest: 38, 30, 18, and 18, respectively.

These business activities were categorized into eight digital transformation themes: profit management, business model innovation, data analytics, security & cybersecurity, reach expansion, regulation compliance, technology investments, and digitization & digitalization. These themes could be regarded as dimensions within a digital maturity model.

The results indicated that the pandemic's effect on the digital transformation of the sector may not be correlated with firm size, as there was no significant difference in the number of business activities between firms listed in the SET 50/SET 100 and those that were not. Additionally, sales performance during the pandemic did not have a discernible impact on the quantity of business activities. However, it is worth noting that firms serving retail customers exhibited a greater number of activities, which aligns with the observation that business-to-business (B2B) companies, especially industrial ones, have historically been slower in adopting digital transformation compared to business-to-consumer (B2C) companies (Angevine *et al.*, 2021).

Our study contributes significant theoretical implications for understanding the dynamics of digital transformation within the business landscape. Specifically, this study offered low-level concepts regarding transformation in the form of business activities, which are rarely included in most maturity models, as noted by Bley et al. (2020). These concepts might be utilized as indicators to measure firms' progress toward the transformation. In the area of data analytics, for instance, one needs to examine whether firms have pursued activities such as data interpretation, data integration, analysis of member data, recruitment and development of data teams, and the use of artificial intelligence solutions.

In addition, our study also added potential dimensions to existing digital maturity models of the sector. We found that some extracted themes aligned with the dimensions proposed in relevant studies, for instance, security & cybersecurity as shown in Boullauazan et al. (2023), data analytics as shown in Kıyıklık et al. (2022), technology investments as were observed in Rakoma (2021), and reach expansion as seen in Modica et al. (2023). Our findings suggested profit management and regulation compliance elements should be added to a fundamental block of the roadmap for digital transformation of firms in the sector. Focusing on profit management emphasized the sector's nature of high fixed costs and significant investment requirements (Banerjee & Deb, 2023). The latter dimension also aligned with the sector's characteristic of being highly regulated (Hamad, 2015). The adoption of digital technologies thus could not ignore the need for compliance at local, national, and international levels, especially in safety, environment, customs, and trade.

Our results suggested significant managerial implications, indicating that incumbent firms could successfully innovate their business models. Traditionally, innovative business models

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in the sector, such as ridesharing services, were predominantly pioneered by digital startups. However, based on our findings, traditional firms could also adapt to digital business models, particularly by embracing the emerging concept of Mobility-as-a-Service (MaaS) (Polydoropoulou *et al.*, 2020). MaaS involved seamlessly integrating mobility services, payment methods, and vehicle advertising to create new value within the value chain. This approach aligned with the online-to-offline (O2O) business model. The O2O concept held particular promise for marketers during times of crisis, as it facilitated reduced physical contact and the creation of novel customer experiences. Potential implementations included offering online payment options and digital route-connected services for passengers, alongside leveraging in-cabin advertising to capture their attention. The emergence of numerous O2O services during the pandemic underscored consumer familiarity and continued intent to utilize them (Yao *et al.*, 2023).

This research had limitations, primarily related to our phrase extraction method. It is possible that not all relevant phrases were adequately captured. Factors contributing to this limitation include the use of a restricted dictionary and verb phrase patterns. In future research, we aim to employ a more effective extraction approach and evaluation method to achieve a more comprehensive list of business activities. Additionally, we plan to incorporate additional data sources to address dimensions of digital transformation, such as firm culture and human resources, which our current study may have overlooked. Moreover, testing our proposed dimensions with companies should help confirm the applicability of these findings.

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Addressing Digital Transformation in Universities

How to Effectively Govern, Trust and Value Institutional Data

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Abstract: In facing digital transformation challenges, universities need to set up their data governance strategies. They include effective solutions to trace and value data about key assets (such as researchers, publications, courses, research projects) scattered across multiple legacy IT systems. As part of an overall solution to deal with the unavoidable data fragmentation and diversity, we provide the complete code of a simple and very efficient framework that can be employed by universities to develop their own knowledge graph, offering a comprehensive picture of the strategic data of the university, such that it can be consistently exploited by different digital services.

Keywords: Digital Transformation, Data Integration, Knowledge graphs, Vocabularies.

Introduction

In pursuing their missions along the three pillars of education, research and societal impact, universities need to find their own way to address the challenges increasingly posed by digital transformation. The term digital transformation usually indicates a set of technological, cultural, organizational, social, creative and managerial changes (McDonald *et al.*, 2012). Digital transformation goes beyond the simple adoption of new technologies and makes it possible to provide services, supply goods, exhibit live experiences, and find, process and make accessible large amounts of content regardless of the real availability of resources, pervasively creating new connections between people, places and things.

Digital transformation in higher education institutions is about the development of new, more advanced and effective methods and practices in pursuit of higher education's mission (Alenezi, 2021). Even though it brings new opportunities, digital transformation also poses new challenges for Communication and IT departments of universities (Maltese, 2018a). Recent studies (Safiullin & Akhmetshin, 2019; Gafurov *et al.*, 2020; Marks & Al-Ali, 2022)

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confirm that universities are not yet prepared, in terms of vision, competency, infrastructures, data strategies and digitalization of their services.

Our work focuses on *digital information challenges*. Universities need to provide to their stakeholders detailed information about a variety of key assets, such as professors, researchers, employees, publications, courses, and research projects. It is, however, difficult for universities to present a complete, up-to-date and coherent picture about them across the different digital communication channels and services employed. For example, it may happen that a certain person is an associate professor according to the human resources system (the main authority for such data), a research fellow on the main institutional portal (the portal is outdated), and a post-doctoral researcher on the department website (the website is not only outdated, but it uses different terminology with respect to the institutional portal).

The root of this difficulty lies in the inherent complexity of the IT university ecosystem (Maltese, 2018b) and it is common to many other large-scale organizations (Gartner, 2014). The diversity of IT systems is actually needed to target specific business processes and key assets with confined responsibility. As a consequence, data fragmentation and diversity (that progressively increase with the number of IT systems employed and the growth of data) bring about a sort of entropic effect where: data about the key assets is scattered across multiple information silos; data differs in format, metadata, conventions and terminology used; data gets duplicated; discrepancies and conflicts increase because different versions and descriptions of the same assets coexist.

Solutions to this problem can be altogether referred to as *data governance strategies*. We report our experience matured during research (Giunchiglia *et al.*, 2012b; Giunchiglia *et al.*, 2014; Maltese & Giunchiglia, 2016; Maltese & Giunchiglia, 2017) and innovation (Maltese, 2018b; Giunchiglia *et al.*, 2022) projects conducted in universities and provided further insights that have been presented during a series of invited talks (Maltese, 2017; 2018a; 2023a; 2023b; 2023c).

Maltese & Giunchiglia (2017) proposed a general solution to address this problem in universities. It stands in addressing *data diversity* via the adoption of well-established Library & Information Science methodologies and tools to curate data and metadata quality, and in addressing *data fragmentation* via the adoption of data integration methodologies and tools.

Maltese (2018b) provides the description of the system architecture, the tools and the digital services that were developed at the University of Trento in Italy in the context of the Digital University initiative and that constitute the first implementation of the general solution. The infrastructure follows the Hub-and-Spoke paradigm. The Hub is an IT system that collects data extracted from various data sources and encodes it as a knowledge graph. This is achieved by means of Extract, Transform and Load (ETL) facilities. In the Extract phase, data is selected from relevant legacy IT systems. In the Transform phase, data diversity is addressed by codifying data uniformly. In the Load phase, data fragmentation is addressed by collecting and pulling together into the Hub data about the same entity (e.g., a single person or a single publication). The knowledge graph provides centralized access to a number of Spokes, each of them being a new IT system expressly developed to support a different digital service. We described the challenges that typically arise (Maltese & Giunchiglia, 2016) and how we addressed them in Italy and in Mongolia (Giunchiglia *et al.*, 2022). Similar issues have been discussed by Rodríguez & Bribiesca (2021), Tungpantong *et al.* (2021), Esmailzadeh *et al.* (2022), Gkrimpizi & Peristeras (2022) and Sułkowski (2023).

The main contribution of this paper is the description and the complete source code of a new data integration framework that we developed in 2021, and that is now publicly available on GitHub (https://github.com/vinmal74/DU). It entirely substitutes the one employed in the first version of the Digital University system developed between 2017 and 2018. It supports engineers in the creation of a multilingual knowledge graph from data extracted from multiple sources. Entirely developed in Java (the previous one required several different technologies, including Java, Scala and Coffee scripts), it makes the development of the ETL facilities much simpler. By changing the entity matching algorithm (that is necessary to detect and merge duplicates) and the data structures employed, it allowed us to overcome the technical challenges described in Giunchiglia *et al.* (2022), thus reducing the time needed to create the knowledge graph by three orders of magnitude with respect to the previous version. In terms of computational complexity, the new algorithm is linear in the number of entities to be integrated, while the previous one was quadratic in the number of entities. It is faster also because of the data structures employed (hash maps), stored entirely in RAM memory (the previous version operated entirely on databases stored in the file system).

In the rest of the paper, we summarize the state of the art, and recall the system architecture and methodology employed, as illustrated in our previous work. We continue with the main contribution of this paper, that is the source code of the new framework for the creation of the knowledge graph at the core of the Digital University solution. Our aim is to provide the methodology and tools such that other universities can replicate our work. Therefore, we provide a demonstrative example of data sources and the ETL code necessary to create the corresponding knowledge graph. The source code, the example and the ETL code are fully available on GitHub. We also illustrate how the knowledge graph can be consistently used by multiple digital services. Finally, we summarize the work done and the future work.

State of the Art and Related Work

Several research communities traditionally address data fragmentation and diversity (Maltese *et al.*, 2009). In the following, we focus on the solutions proposed by Business Intelligence (BI) and Library & Information Science (LIS).

The primary purpose of BI is to support decision-making in organizations (Buchanan & O'Connell, 2006). Data-driven decision-making refers to the practice of basing decisions on the analysis of data rather than purely on intuition (Brynjolfsson *et al.*, 2011). Therefore, data needs to be appropriately collected and prepared. To this end, data integration is a fundamental technique in BI to tackle the initial data fragmentation and diversity. In fact, data integration is a process that combines data from different sources and provides users with a uniform view of the data (Lenzerini, 2002). Two main alternative approaches exist. In federated systems, data is logically combined at query time. In centralized systems, data is physically combined in a data warehouse via ETL procedures. The Extract phase deals with the selection, assemblage, analysis and processing of data. The Transform phase takes care of converting data into a standard format. The Load phase imports data into the data warehouse. The centralized approach ensures there is one trusted proxy providing data in a timely manner and uniformly. Data warehousing is a fundamental tool of BI, and metadata plays a key role because of the complexity of the data migration process (Watson & Wixom, 2007).

Library Science is traditionally concerned with archiving texts and organizing storage and retrieval systems to give efficient access to texts (Denning, 2003). LIS is the technical and technological innovation of Library Science that employs information technology for documentation and library services (Buckland, 1996). Libraries have a strong tradition in data and metadata curation, especially in terms of standard data models for the representation of intellectual and artistic creations (O'Neill, 2011). Metadata about them includes title, subject, and authors. Authority control makes sure that each entity is assigned a unique header, such that each entity can be uniquely identified and referred to (O'Neill, 2011). Unique headers include names and alphanumeric identifiers. Similarly, vocabulary control enforces the usage of standard terms to unambiguously refer to each subject (Zeng *et al.*, 2011). In controlled vocabularies, standard terms are arranged hierarchically from broader to narrower terms (ISO 2596-1:2011). Altogether, the adoption of these practices enables controlling diversity and obtaining high quality data that in turn ensures high precision and recall in search. Data fragmentation is addressed in libraries by employing standard data exchange protocols, such as the OAI-PMH framework (Sompel *et al.*, 2004) and by adopting solutions to map equivalent concepts in different knowledge organization systems (ISO 2596-1:2011; Giunchiglia *et al.*, 2009; Maltese *et al.*, 2010; Giunchiglia *et al.*, 2012a).

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A few initiatives have provided solutions to support storing, searching, browsing, visualizing and sharing scholarly data. VIVO (Börner *et al.*, 2012) relies on Semantic Web technologies to represent and store data in the RDF standard model (https://www.w3.org/RDF/) and retrieve it using the SPARQL query language (https://www.w3.org/TR/rdf-sparql-query/). However, it has been observed that these initiatives offer limited support to tackle data diversity and data fragmentation (Maltese & Giunchiglia, 2017). In fact, they do not provide effective entity matching tools and methodologies to effectively control and enforce terminology.

Our approach is compliant with other solutions designed for universities, such as VIVO, and for digital libraries, such as DSPACE (Smith *et al.*, 2003). For instance, a converter can be easily developed to translate our knowledge graph into the VIVO model and ontology, so that it can be exploited by VIVO applications, such as the VIVO portal. Our framework makes the creation of the knowledge graph simple and very efficient.

The System Architecture

The system architecture adopted in Trento (Figure 1) was first introduced in Maltese (2018b) and described further in Giunchiglia *et al.* (2022). The knowledge graph is built by reusing data that becomes available through ETL facilities, and it is employed in a Hub-and-Spoke architecture. Each spoke supports a different digital service. The idea is that new Spokes are added incrementally whenever there is a need for a new service which cannot be provided by the existing Spokes.

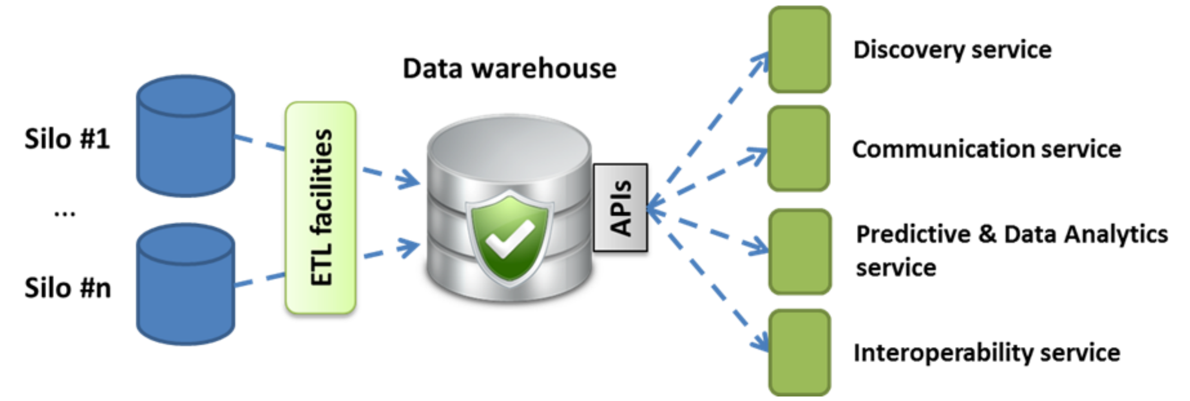

Figure 1. The system infrastructure of Digital Universities

This architecture was chosen as it represents a more efficient and scalable alternative to point-to-point communication in that the number of connectors between IT systems is reduced drastically, thus reducing complexity and maintenance costs (Hopkins *et al.*, 2015).

The Hub collects data extracted from various data sources (Extract), encodes data according to a uniform model and terminology (Translate), and creates a knowledge graph through an integration framework (Load). Through dedicated Application Programming Interfaces (APIs), the Spokes get access to the knowledge graph stored in the Hub.

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Overall, the Hub fulfils the following requirements (Maltese, 2018b).

- **The Hub provides centralized access to data** natively stored in the heterogeneous data sources (different schema, model and format) managed by legacy IT systems. This separation of duties is necessary to ensure that legacy systems can continue to function as usual, thus benefitting from advantages (contained costs, dedicated business processes, focused data, dedicated users and confined responsibilities) that come from their vertical end-user applications. Relevant data about the key entities that are necessary to support the centralized services is reused in the Hub by means of ETL facilities. They ensure that data about the same entity extracted from multiple sources is appropriately collected, transformed, merged and correlated. Especially, entity matching (e.g., Wang *et al.*, 2011) and merge facilities are essential to avoid the presence of duplicates.
- **The Hub supports knowledge and language localization**, in that the knowledge graph is built according to a local customized data model and terminology. Localization can take place starting from a reference data model (the knowledge) and vocabulary (the language) designed specifically for universities (Maltese, 2018b). Their main purpose is to provide a common core of entity types, properties and terminology in multiple languages necessary to fulfil typical services of a university and to favour interoperability among them, similarly to what is done by VIVO. Simultaneously, the different needs across the globe demand the capability of the system to support their customization and extension as required locally by the digital services of a certain university.
- **The Hub supports the development of centralized services** via dedicated APIs that provide access to the knowledge graph. APIs support the development of university services on the Spokes such that they can consistently query the Hub and exploit the same content, i.e., the knowledge graph. They include: (a) *Discovery services* supporting browsing and search (Giunchiglia *et al.*, 2014); (b) *Communication services* conveying information to stakeholders uniformly and consistently across different communication channels (Maltese, 2018b); (c) *Predictive & data analytics services* supporting decision-making processes (Waller & Fawcett, 2013; Brdesee, 2021); (d) *Interoperability services* supporting the import/export of data from/to existing standards, such as the publication of Open Data (Tran & Scholtes, 2015), or according to the VIVO model and ontology, or to answer queries across federated universities.

Among other things, in our previous work (Maltese, 2018b) we described how we comply with Intellectual Property Rights (IPR), licensing and privacy concerns and guarantee secure access to data. In terms of IT security, we selected technologies by making sure that they satisfy security levels demanded by Italian law. Our IT staff constantly ensures that adequate security measures are in place. Data sources and system components are secured and not accessible from outside of the University intranet. Access to them is granted to administrators only. Data is accessed exclusively via database views expressly arranged to provide access to relevant data only. Among other things, this makes system maintenance easier in that such views can be seen as *contracts* that cannot be violated even in the case that the data source changes, e.g., because of an update of the corresponding IT system. Regular backups guarantee data integrity.

To protect the privacy of users, and to be compliant with the General Data Protection Regulation (GDPR), in designing and developing the system and the services we followed well-established privacy-by-design principles (Hoepman, 2014), suggested also by the European Data Protection Supervisor (2018). Our privacy policies are publicly available. Only relevant and non-sensitive data is managed. Data is stored in separate indexes in order to prevent unwanted correlations. Each Spoke receives only the data that is strictly relevant for the digital service it supports. In terms of IPR, we promote and support Open Science principles by allowing the download of scientific publications of our researchers with Creative Commons licenses through the institutional portal we developed.

The Methodology

The methodology, introduced in Maltese & Giunchiglia (2017) and refined in Giunchiglia *et al.* (2022), defines an iterative process composed of sequential steps, briefly outlined below, which are followed every time a new digital service needs to be designed and developed. In our previous work, we illustrated its advantages that include scalability, cost-effectiveness, and facilitated compliance with legal constraints.

Step 1. Collecting service requirements. It consists of collecting the requirements of the new service in terms of functionalities, target users and necessary data.

Step 2. Knowledge localization. The reference data model, providing the schema which is enforced to store the knowledge graph in the Hub, is adapted to local needs. It is constituted by entity types and properties necessary to describe typical key entities of universities, such as people, courses, publications, dissertations and research projects. Chatterjee *et al.* (2016) presents a methodology that can be followed to design the data model in a given domain. It should include identifiers, i.e., those properties necessary to identify unequivocally an entity of a certain type such that entity matchers can work properly (Bouquet *et al.*, 2007). Knowledge adaptation means adding or specializing entity types and properties that are necessary to support the new service.

Step 3. Language localization. The controlled vocabulary is adapted to local needs. We employ well-established LIS methodologies for vocabulary development (Maltese, 2018b). For instance, the vocabulary should provide the terminology necessary to describe the various positions occupied by people (e.g., full professor, associate professor, researcher), the kinds of publications (e.g., journal article, conference paper), the status of a research project (e.g., submitted, approved). Language adaptation means adding or specializing

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concepts, selecting preferred terms from the vocabularies or adding new languages that are necessary to support the new service. This includes handling lexical gaps (Giunchiglia *et al.*, 2018), i.e., concepts which do not have a precise translation in the target language. We address language diversity by representing knowledge as language-independent concepts whose meaning is approximated in each language by means of terms that are the closest in meaning.

Step 4. Data hunting. The legacy IT systems are assessed in order to identify the possible sources for the data required by the service. The following cases can arise: (a) there is only one system that can provide them; (b) multiple systems, possibly maintained by different departments, can provide part of them, which can eventually partially overlap or even be in conflict; or (c) existing systems cannot provide all of them. In the latter case, it is necessary to develop new IT systems able to complete missing data.

Step 5. Building the knowledge graph. ETL facilities are implemented in order to Extract and Translate data according to the localized knowledge and language, and to Load them into the Hub. Mechanisms to resolve conflicts in data may include authority (based on the ordering of importance of the sources) or voting (based on the majority of the sources) schemes (Dong & Naumann, 2009). Overlaps are handled through entity matching and merging techniques. This task requires an adequate infrastructure able to semi-automate the process and to keep the Hub aligned with the sources, by running ETL facilities regularly (e.g., daily). Especially, human intervention is required to fix mistakes in data (whenever possible, they should be fixed in the data sources), accommodate for missing terms in the controlled vocabulary (thus requiring an extension of the vocabulary) and when the schema of the data sources changes (e.g., an attribute was supposed to have n possible values and the (n+1)th value appears). Fixes are recorded and applied automatically in the next updates (Giunchiglia *et al.*, 2021).

Step 6. Implementing the service. The service is implemented and deployed by accessing the knowledge graph data from the Hub via dedicated APIs.

The Digital University Framework

The framework we developed to support the creation of the multilingual knowledge graph is fully available at https://github.com/vinmal74/DU/tree/main/src/Hub.

The framework is simple in that it is entirely developed in Java, it is constituted by less than 300 lines of code, and it is based on the well-known object-oriented programming paradigm. The Entity Relationship model (Chen, 1976) is employed to represent the various entities and how they are interconnected. The ETL paradigm, which is typical of data warehousing approaches to data integration (El-Sappagh *et al.*, 2011), is employed to extract data from the original data sources, to convert them into entities, and to incrementally construct the knowledge graph. Such simplicity allows any programmer, with no specific knowledge of representation languages and Semantic Web technologies, to adopt it very quickly and easily.

The framework is very efficient for two reasons. The first is that the data integration algorithm is linear in computational complexity. In fact, it employs hash maps to store and retrieve the entities: insertion and retrieval in hash maps takes constant time. The second is that all data structures are stored in RAM memory to guarantee the maximum performance at runtime.

For instance, the knowledge graph of the University of Trento is currently constituted by around 225,000 entities, appropriately selected. Entity types are Person, Organization, Role, Course, Project, Thesis, Publications, and Files. The creation of the knowledge graph takes 2-3 minutes (depending on the network load, given that datasets are located on different servers) on a laptop equipped with an Intel Core i5-7200 dual core 2.50 GHz and 2.71 GHz, and 8 GB of RAM memory. The total memory usage is around 370 MB.

The framework consists of 10 Java classes. Figure 2 provides an exemplification of the data structures used to represent the knowledge graph. It shows three entitybases and three entities interconnected between them. The mapping between the classes of the framework to the standard W3C RDF schema (https://www.w3.org/TR/rdf-schema/) is trivial.

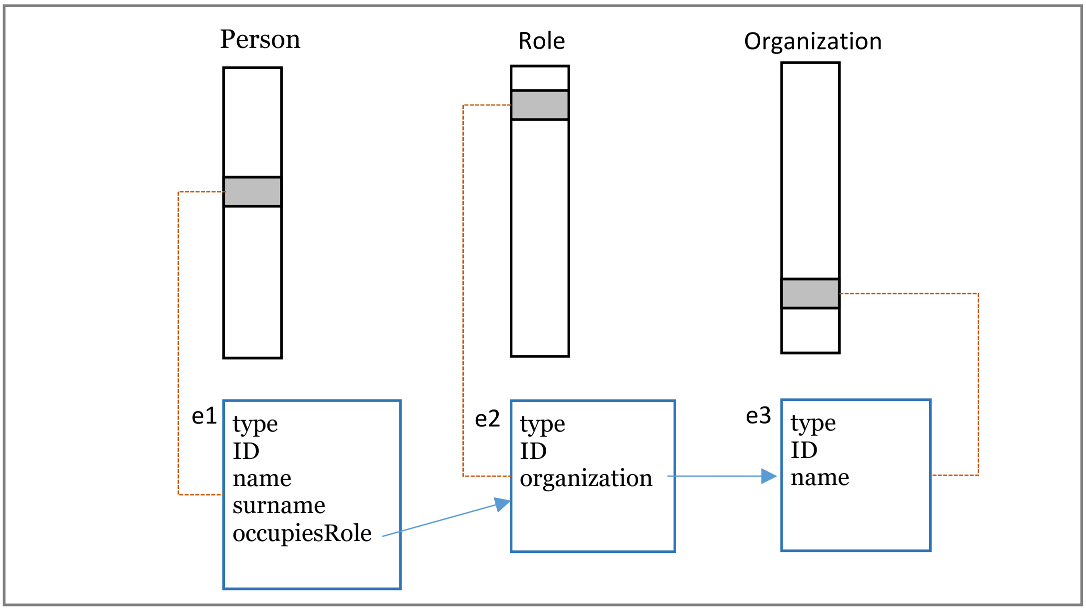

Figure 2. An exemplification of an entityStore

The knowledge graph is represented as a set of **entitybases** (Entitybase.java), one for each entity type required. Within each entitybase, we employ a HashMap. We represent entity types as an integer. We suggest that types could be encoded as constant values, e.g., Person = 0, Organization = 1, Role = 2, Course = 3. Each **entity** (Entity.java) is characterized by its type, a unique identifier (that we represent as a String) and a set of attributes.

Attributes (Attribute.java) are <name, value> pairs. The current framework supports three different types of attributes. Java classes can be extended to support additional types. **String attributes** (StringAttribute.java) are language independent attributes whose value is stored as a String; numbers and dates are converted into strings. **Relational attributes** (RelationalAttribute.java) represent relations between entities; in fact, their values (EntityValue.java) are <type, id> pairs, where type is the entity type and id is the identifier of the target entity. **Concept attributes** (ConceptAttribute.java) are language-dependent attributes whose values (ConceptValue.java) are stored as a Concept (that are simply represented as integers) used to codify values whose labels need to be read according to the languages used, e.g., in English and Italian.

In order to represent concepts in specific languages, it is necessary to define corresponding **vocabularies** (Vocabulary.java). Each vocabulary is characterized by a reference language and a list of **concepts** (Concept.java). Each concept is a triple <id, label, definition>. For example, the concept of researcher in English is given by the triple <56569, "researcher", "(role) a person who conducts research activities">, while in Italian it is given by <56569, "ricercatore", "(ruolo) una persona che svolge attività di ricerca">. Following the ISO 25964 standard for vocabulary representation (https://www.iso.org/standard/53657.html), the identifier must obviously be the same in all vocabularies. The definition is needed to keep track of the meaning of the labels.

The current framework has two main limitations. The first is that it may need significant amount of RAM in case of datasets of huge size. For the purposes we envisioned in Trento (see Using the Knowledge Graph in Multiple Digital Services below), the RAM memory used is actually approximately 370 MB only. Such cheap usage of memory is possible because we only select relevant data to be extracted from the datasets. The second limitation is that it may require an extension of the entity-matching libraries in case not all sources already provide unique identifiers for all entities or in case similar entities are stored in different datasets with different identifiers. We overcome this limitation by making sure that identifiers are always available for all entities, either as a single attribute, or as a result of a combination of multiple attributes.

The Demonstrative Example

Suppose we want to develop a university portal in two languages, English and Italian, whose functionalities have been identified by collecting requirements from various stakeholders. The local data model will have to define the various entity types and their attributes necessary to accommodate such requirements. For instance, it may establish that a Person must have name, surname, gender, email, phone and set of positions occupied in administrative units. For sake of simplicity, we assume that data sources have been already pre-processed (for instance, as a result of a job that runs daily in order to get up-to-date data) and available as CSV files (see https://github.com/vinmal74/DU/tree/main/src/data):

- **people.csv** contains the people affiliated to the University;
- **units.csv** contains the administrative units of the University;
- **types_of_units.csv** contains information about the types of administrative units;
- **positions.csv** contains information about the affiliations of each person;
- **types_of_positions.csv** contains information about the types of positions that can be appointed to people in the administrative units;
- **courses.csv** contains information about the courses offered.

The two vocabularies are stored in TXT files. Each row contains the identifier of the concept, the label and the definition in the corresponding language. They can be extended as needed. Figure 3 provides a fragment of the content in the English vocabulary.

```
118     | person               | a human being
52974   | rector               | (role) the head of a university
53485   | director             | (role) the person in charge of managing a department or directorate
118272  | deputy director      | (role) the person appointed to represent or act on behalf of the director
56251   | president            | (role) primary leader of a firm or corporation
54235   | director general     | (role) the manager with the highest ranking
53282   | coordinator          | (role) the person responsible for coordinating the activities
54173   | full professor       | (role) a professor of first rank in a university
52409   | associate professor  | (role) a professor of second rank in a university
56569   | researcher           | (role) a person who conducts research activities
118261  | PhD student          | (role) a student who is enrolled in a doctorate school
118264  | staff                | (role) the people responsible of the administrative and technical tasks
43544   | organization         | a group of people who work together
44331   | administrative unit  | an organization regarded as part of a larger social group
45010   | statutory body       | an institutional unit defined by the statute
45016   | governing board      | a board that manages the affairs of an institution
118249  | supporting board     | a board that supports the governing body of an institution
44452   | division             | an administrative unit of second level in government or business
45084   | office               | an administrative unit of basic level in government or business
43989   | academic department  | a division of a university or school
35792   | degree program       | a course of study leading to an academic degree
4553    | course               | education imparted in a series of lessons or meetings
```

Figure 3. Example of content of the vocabularies (in English)

Developing the ETL Facilities

In this section, we present a demonstrative toy example of how the knowledge graph can be built by implementing ETL facilities and by employing the framework. It is fully available on GitHub at https://github.com/vinmal74/DU/tree/main/src/ETL.

The main functionality offered by an entitybase is data integration, supported by the load method (see Entitybase.java). As from the example in Figure 4, suppose we extracted enough data to generate the entity e1. In loading the entity e1 in the entitybase E, if E already contains an entity e2 with the same identifier, the set of attributes of e1 are merged with those of e2, thus obtaining the entity e3; otherwise e1 is loaded in E as it is.

e1		e2		e3	
type	**= 118**	**type**	**= 118**	**type**	**= 118**
ID	**= 1000099**	**ID**	**= 1000099**	**ID**	**= 1000099**
Surname	= Sordi	Email	= alberto.sordi@unitn.it	Surname	= Sordi
Name	= Alberto	Phone	= 2005	Name	= Alberto
Phone	= 1000			Email	= alberto.sordi@unitn.it
				Phone	= [1000, 2005]

Figure 4. Example of data integration

Two attributes are considered to be different when the name or the value do not match. In the current implementation, both the entity matching and the attribute functions simply rely on the standard equality operator, but, according to the specific scenario, it could be a more complex similarity function (Köpcke & Rahm, 2010), e.g., to accommodate approximation of values.

Thus, a data integration pipeline can be designed as a set of ETL facilities where for each data source a dedicated facility extracts data (E), translates it into a set of entities (T), and loads each of them in the corresponding entitybase (L). Given that the load function is characterized by O(1) computational complexity, the complexity of the ETL algorithm is O(n), where n is the number of entities identified in the data sources.

In the following, we describe the code of the data integration pipeline. Individual entitybases are stored in an **EntityStore** (EntityStore.java). We implemented them as an array. The toy example requires four entitybases: EB[0] for Person, EB[1] for Organization, EB[2] for Role, EB[3] for Course.

The **data integration pipeline** (ETL.java) contains the main method. It creates the English and Italian vocabularies by loading the two TXT files that contain the <id, label, definition> triples, and initializes the EntityStore. Finally, it launches four different ETL facilities to process the CSV files with the data sources and to incrementally construct the knowledge graph. They can be executed in any order, thus always obtaining the same result.

The first ETL facility (People.java) processes people.csv. Below we exemplify how, for the first row of people.csv, it creates one entity of type person to be loaded in EB[0]. Here 118 and 90013 are the concept IDs for “person” and “male”, respectively, in the vocabularies. Class is the attribute that can be used to specialize the type, that in this case remains “person”.

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type **= 118**
ID **= 1000099**
Class = 118
Surname = Sordi
Name = Alberto
Gender = 90013
Email = alberto.sordi@unitn.it
Phone number = 1000

The second ETL facility (Units.java) processes units.csv. Below we exemplify how, for the first two rows of units.csv, it creates two entities of type organization to be loaded in EB[1]. Here, 43544, 44834 and 45016 are the concept IDs for "organization", "university" and "academic senate", respectively, in the vocabularies. The latter two are taken from types_of_units.csv. The Class attribute specializes the type "organization".

type **= 43544**
ID **= UNIT00001**
Class = 44834
Name = University of Trento

type **= 43544**
ID **= UNIT000002**
Class = 45016
Name = Academic Senate
Part of = (1, UNIT00001)

The third ETL facility (Positions.java) processes positions.csv. Below we exemplify how, for the first row of positions.csv, it creates three entities. The first entity is of type person to be loaded in EB[0], and corresponds to the same person with ID 1000099 created above; it is therefore merged with the first version of the same entity previously loaded in EB[0], thus adding the relation Occupies Role. The second entity is of type organization to be loaded in EB[1], and corresponds to the same organization with ID 43544 created above; it is therefore merged with the first version of the entity loaded before in EB[1], but no additional attributes are added. The third entity is of type role to be loaded in EB[2], where 118247 is the concept ID for "role" and the type of position occupied OTHEXT001 is converted into 118264, which is the concept ID of "other staff" (see types_of_positions.csv) that becomes the value of Class. We represent roles similarly to Jureta *et al.* (2007).

type **= 118**
ID **= 1000099**
Occupies Role = (2, UNIT000002_118264)

type **= 43544**
ID **= UNIT000002**

type **= 118247**
ID **= UNIT000002_118264**
Class = 118264
Organization = (1, UNIT000002)

The fourth ETL facility (Courses.java) processes courses.csv. Below we exemplify how, for the first row, it creates three entities. The first is of type person to be loaded in EB[0]. The second is of type organization to be loaded in EB[1]. The third is of type course to be loaded in EB[3], where 4553 is the Concept ID for “course”.

type = **118**
ID = **1000313**

type = **43544**
ID = **UNIT08624**

type = **4553**
ID = **90065**
Class = 4553
Name = Administrative Law
Degree program = Law (LM5)
Department = (1, UNIT08624)
Professor = (0, 1000313)

Using the Knowledge Graph in Multiple Digital Services

Once the knowledge graph has been created, it needs to be stored somewhere. In Trento, we store it in Elasticsearch indexes (https://www.elastic.co/what-is/elasticsearch), a distributed, free and open search and analytics engine for all types of data that offers simple, very efficient and scalable REST APIs to store and query data. On top of Elasticsearch, we then developed an additional layer of RESTful APIs that are used by the various digital services.

To export the knowledge graph, the EntityStore offers the toJSON function that converts an entity into a JSON object. It takes as input the identifier of the entity, its type (to identify the entitybase in which it is contained), the vocabulary to be used to translate concept attributes (for instance, the Italian vocabulary), and the depth of the knowledge graph to be taken, i.e. the maximum number of relations to be followed. As an alternative, you can directly use the get functions offered by the Java classes.

So far, in Trento we have designed and developed four digital services that access to the same knowledge graph.

The **institutional portal** (https://webapps.unitn.it/du/en) is a public communication service that offers a comprehensive webpage (from the integration of 7 different data sources) in English and Italian for each of the University members, academic departments, governing bodies and administrative units. University members include academic staff (professors, researchers, PhD students), administrative and technical staff, and university executives. It is visited by around one million users per year.

The **institutional dashboard** is a data analytics service providing insights about the quality of research conducted by the faculty members with a focus on publications and research projects. It provides statistics and interactive graphs useful to examine trends, strengths, and points of improvement. Access is reserved to University members only via credentials.

Dedicated APIs have been developed for the **publication of Open Data** on the regional (https://dati.trentino.it/organization/universita-di-trento), Italian (https://www.dati.gov.it) and European (https://data.europa.eu) data portals. With this interoperability service, we comply with national guidelines about sharing public sector information.

The **University Mobile App** (https://unitrento.app/) is a communication service that has been developed by the IT staff of the University for its students. The knowledge graph is one of the data sources used and is accessed through dedicated APIs.

Conclusions

Digital transformation poses new challenges for universities. They need to tune their strategies for effective data governance and identify efficient solutions to trace and value information about their key assets scattered across multiple IT systems. As part of an overall solution to deal with the unavoidable data fragmentation and diversity, we illustrated the work done in Trento where we designed and implemented an infrastructure based on the Hub-and-Spoke paradigm. In this paper, we presented the new framework and the ETL facilities that we developed in 2021 to construct our knowledge graph more efficiently and easily than in the first version. The knowledge graph is used consistently by different digital services. We hope that the source code provided here can be of inspiration and can be employed by other universities to develop their own knowledge graphs and digital services.

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Barriers to Digital Transformation

The Case of Moroccan Companies

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Abstract: Digital transformation, combining advanced technologies and innovative processes, represents a major revolution in the managerial landscape of companies, likely to stimulate growth and efficiency. However, the obstacles to this transformation are numerous and interrelated. The objective of this article is to shed light on the nature of these obstacles in the Moroccan context. Based on a survey of 312 Moroccan companies and 74 interviews, this study made it possible to determine the major obstacles to digital transformation. The major barriers to digital transformation are essentially the lack of internal resources and skills, resistance to change and lack of leadership, insufficient return on investment, the strategic and procedural complexity of the project, security problems, and the inconsistency of the transformation project to be carried out. These results confirm those obtained by other studies under other skies, thus making it possible to conclude that the nature of the obstacles to digital transformation remains practically the same in the different countries covered by similar research, but only the degree of their prevalence changes. Having an idea of the significant barriers will help managers increase their digital and organizational performance.

Keywords: Digital transformation, barriers, digital investment, Morocco.

Introduction

Half of the Fortune 500 companies in 2000 are now extinct (Berman, 2019). Many of these companies have one thing in common: they have not undertaken the necessary digital transformation that has marked our last two decades.

Digital transformation is a major challenge for the competitiveness and sustainability of organizations, as well as for the growth of the economy in general (Abbu *et al.*, 2021; Adarov *et al.*, 2022; European Investment Bank, 2022; Foerster-Metz *et al.*, 2018). Becoming a survival transition instead of a fad (Mahboub & Sadok, 2022), digital transformation, as many

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companies understood, plays a crucial role, which has led to an interesting amount of investment and reorientations. However, the return on these investments is not always easy to understand and estimate, especially since the digital transformation project includes a set of obstacles that limit the proper implementation and optimization of performance (Diener & Špaček, 2021; Solow, 1956). It is in this context that few studies and scientific articles have attempted to explore the theme of barriers to digitization.

For an organization, investing in digital is not just about acquiring and deploying cutting-edge technologies. It involves a total change of culture and vision of the world and requires rethinking the very foundations of the system. To prepare for this transition, organizations must meet a major challenge: identify the obstacles and overcome the habits and practices that hinder organizational evolution.

It is with this objective that this article proposes to contribute to a better understanding of the main obstacles that threaten digital transformation. It synthesizes the existent literature, which remains limited, on barriers to digital transformation (DT), and, by combining them in our paper, it serves as an integrative approach guiding future research in this area. A particular focus will be on the case of Morocco where, with regard to its level of technological maturity, the barriers to DT are little studied. However, a better analysis of these issues will allow decision-makers to better overcome the obstacles of digital transformation, considered an essential lever for better development.

To this end, this article will be presented as follows: after sketching a literature review on the digital transformation barriers, we then outline the methodology used to answer this research question: **what are the main barriers to digital transformation?**
The last section gives rise to a presentation of the main results of our survey and their implications in the Moroccan context, before concluding with a discussion on the lessons learned, the limitations, and the research perspectives of our work.

Literature Review

Digital transformation (DT) refers to the adoption and use of disruptive technologies to increase productivity, value creation, and social well-being (Ebert & Duarte, 2018). As a complex task, digital transformation encompasses changes in management, leadership, culture, technological adoption, acceptance of innovation, and digitalization of resources (Francis *et al.*, 2018), leading to efficiency, flexibility, automation, better decision-making, and more collaboration (Foerster-Metz *et al.*, 2018; Sadok, 2021).

Most companies adopt this new paradigm principally for customer experience improvement, efficiency increase, and cost reduction (Mahboub & Sadok, 2023; Weill and Woerner, 2018).

http://doi.org/10.18080/jtde.v12n1.814

However, according to the study carried out by Kemp, Schot & Hoogma (1998), it turns out that the acceptance of new technology and the appropriation of its benefits depends on the ability of the organization to integrate this technology optimally into the existing system. However, several recent studies highlight the mismatch between digital investments and a company's overall strategy (Nwankpa & Merhout, 2020). A study by consulting firm McKinsey found that 70% of digital transformation investments fail (Nwankpa & Merhout, 2020). Another survey confirms this result by finding that barely 50% of companies have successfully implemented their digital investment correctly, while 20% consider their investment in digital transformation to have been a waste of time and resources (WIPRO Digital, 2017). Another global survey of more than 16,000 companies conducted between 2015 and 2016 on investments in digital transformation revealed that digital gains are not sufficiently rewarded (WEF, 2017). These studies reveal that, despite significant advances in theoretical and practical research on corporate DT, the fact remains that the results obtained from digitalization are still unsatisfactory. This lack of optimality in this organizational transformation resides not only in the non-efficiency of this type of investment, but also in all the barriers hindering the quest for optimality (Benkhayat *et al.*, 2015).

Indeed, even if studies on the obstacles to the implementation of digital technology represent the main problem of several studies (Chan, 2008; Chan *et al.*, 2018; Greiner & Franza, 2003; Hillary, 2004; Hon & Millard, 2018; Post & Altma, 1994; Quazi, 1999; Richardson & Lynes, 2007; Shairullizan KamalulAriffin *et al.*, 2013; Vachon & Klassen, 2006; Williams *et al.*, 2010; Zhang *et al.*, 2011), the fact remains that the latter still remain generic about the determinants of this failure once the investment in digital transformation is initiated.

According to El Alami *et al.* (2015) and Hon & Millard (2018), the lack of alignment and optimality of the implementation of these new technologies represents one of the main limits: it is no longer a question of simply developing the digital transformation strategy (DTS), to update the business model, to invest in the elements necessary for the conduct of the digital transformation project, but to ensure the synchronization of the stakeholders and the adequacy of all the elements required to succeed in this digital shift. The study conducted by Hon & Millard (2018) showed that resistance to the adoption of digital is also explained by the fear of losing control of data, and therefore power within the organization, or by a conservative organizational culture. Indeed, resistance to change is a fairly well documented barrier in the literature during any type of decision-making, because it generates a fearful organizational shift towards uncertainty (Coghlan, 1993), but also because it represents a disruption of the established comfort zone (Keyes, 2000).

Digital transformation induces major changes in our lifestyles and our way of working and interacting with others. Consequently, digitalization appeals to culture in the sense that new

http://doi.org/10.18080/jtde.v12n1.814

technologies require more innovative techniques in the way of operating. From now on, it is more a cultural subject than a technological one, since the digital revolution influences the daily lives of all the parties involved in the company (Bozkus, 2023). Successful decision-making immediately arouses a collective intelligence that gives rise to new cultural approaches.

Conversely, employees can be disoriented by new challenges imposed by their hierarchy without their involvement. This sometimes results in transformation processes generating resistance from employees when the associated teaching method is inadequate. However, the barriers to DT's success do not end with cultural change. There are myriad other factors, such as lack of strategy, inadequate and misaligned corporate structures (Gupta, 2018), poor ROI visibility, innovation cannibalization (Christensen, 1997; Ebert and Duarte, 2018), lack of preparation of organizations, silo structure and lack of agility (Hughes, 2017), poor communication, rigidity and clutter of rules and formalization (De Smet and Gagnon, 2018), lack of skills for satisfactory value creation (Van der Bel, 2018), and aversion to transparency (Sadok, 2023).

Further studies on the main barriers to digitalization, such as that of Gupta (2018), conclude that the main obstacles to DT are blurred vision, misunderstanding and lack of management experience, an inflexible culture, the lack of digital leadership skills, unclear measurement of results, and employee resistance to change. The work of Kohnke (2017), on this same issue, concludes that the main obstacles to the success of a digital project are the lack of a sense of urgency, unclear roles and responsibilities, the lack of internal talent to carry out digital projects, and a rigid organizational culture and structure. To this, we must add other external obstacles, such as regulation, the obscurity of the contributions of digital to the company, the shortage of skills and the lack of qualifications, and the low access to financing (Ebert & Duarte, 2018). The MIT study (Kane *et al.*, 2015) synthesized all these factors by classifying these barriers in relation to the company's level of digital maturity.

Table 1. Principal barriers by maturity level

	Early	**Developing**	**Maturing**
Top Barriers	Lack of strategy	Too many priorities	Too many priorities
	Too many priorities	Lack of strategy	Security concerns
	Lack of management understanding	Insufficient tech skills	Insufficient tech skills

Source :(Kane *et al.*, 2015)

In this same trend, the work of Post & Altma (1994) divides the barriers to digital implementation into two main categories: industrial barriers and organizational barriers. Industry obstacles include investment costs, technical information, current configuration of operations, competitive pressure, and industry regulations; while organizational barriers relate to past practices, poor communication, employee attitudes, and inadequate leadership (Chan *et al.*, 2018). Hillary (2004) also analyzed the obstacles to digital transformation and identified 48 factors, which he classified into eight dimensions: resources, implementation, understanding and perception, attitude and corporate culture, support and advice, certifiers/-auditors, and economic and institutional weaknesses (Chan *et al.*, 2018). The latter authors have also classified these barriers into three main categories: barriers related to products and/or services, external barriers, and internal barriers.

In their exploratory study of a particular sector of the economy, namely the banking sector, Diener & Špaček (2021) identified the main obstacles to digital transformation. Their work presents a description of the industrial and organizational obstacles from 34 interviews, which we can present as shown in Table 2.

Table 2. Organizational barriers blocking digital investment and transformation

Main Category	Barriers	Description
Benefits	No public funding	The government believes that companies have sufficient financial resources to carry out their digital projects. Therefore, no public support is provided, since it is not required.
Customer	Acceptance	Some customers reject some aspects of the digital transition due to their lack of trust in the technology (intangible money and transactions).
	Usage concerns	Some customers are not always able to use the digital tool, even if they are convinced by its advantages. Others cannot take full advantage of it and need continuous clarification and support.
	Age structure	The difference between the ages of customers leads to different knowledge and expectations towards digital technology and its use.
	Usage behaviour	The age and perception of bank customers lead to various usage behaviours. Juniors are, in general, more comfortable with digital banking, while seniors tend between physical and phygital banking.
	Expectations	While some customers prefer the permanent availability of technology and to maintain the availability of personal consultants, others do not but tend more likely to reach for security concerns.
	Knowledge	Despite the availability of information, customers need further knowledge and clarifications for a successful digital transformation project.
	Switching behaviour	With the digital transition, customers have more openness and better access to information. This allows them to compare competitors' offers and can reduce their loyalty.
Employee	Resistance to change and transparency	Digital transformation leads to reducing the number of employees with the maintenance only of the necessary talents. It also requires important changes in the working mode (more openness, the culture of sharing etc.). This situation creates worries, fears, and dissatisfaction among employees, which is translated as resistance.
	Flexibility	The lack of flexibility and fast response of employees to the digital transition limits the project's conduct.

Main Category	Barriers	Description
	Qualifications and friendliness	The friendliness and lack of competencies of the employees reduce the quality of the digital transformation project, and therefore, lack of alignment with the enterprise's complex changes.
	Age structure	The age difference leads to different behaviours and perceptions. Juniors have an advantage over Seniors since they grow up with technologies and know how to use them.
Knowledge and product	Product and bank complexity	Based on the product/service proposed, the physical or digital form is to be offered.
Market	Market situation and competitive pressure	Due to the high uncertainty and competitiveness in the market, organizations are confused between investing in the customers or the competitors' change and assuring the enterprise's survival.
Strategy/management	FinTech	The strong development of FinTechs and their mastery of the core activities can lead to mortality or a performance decrease.
	Reputation worries	Enterprises are distant from an optimal DT investment since they are afraid of the reputational consequences of project failure.
	Reaction speed	The reduced reaction speed of companies to the digital transition (less than FinTechs) limits their success.
	Digital Transformation Strategy (DTS)	Many DT projects fail due to the absence of a DTS. Managers confirm that its formulation and implementation represent one of the major existential challenges faced.
	Corporate culture	The resistance to changing the corporate culture threatens the DT project. A successful digital transition requires a culture update.
	Resources	The lack of financial and non-financial (technological, competencies, structure) resources is a DT limit. It can be available in the bank but either is used for other concerns or does not cover the whole costs of the project.

Source :(Diener & Špaček, 2021)

Despite the empirical validation of this previous work, it remains necessary to further explore the main obstacles to digital transformation to help lay the foundations for a procedural understanding of the implementation of an accomplished digital transformation.

Moreover, studies on DT barriers in the Middle East and North Africa (MENA) region remain rare. In general, studies on this theme in developing countries are quite rare and little explored in the literature. These are the main aims that we tackle in this work.

Methodology

The methodology used to study the barriers of digital transformation consists of data collection in the form of a survey. It is a quantitative method that applies to a sample that will allow us to draw statistical inferences from the processing of a questionnaire resulting from a field survey (Creswell & Creswell, 2023). In the absence of a database dealing with the facts to be studied to elucidate elements of understanding of the problem, this collection of information would make it possible to remedy this lack of data.

We have supplemented the questionnaire method with individual interviews. Nominal variables, measured by a Likert scale, were used to approximate people's attitudes and opinions on DT topics. In the methodology we used, it is the number of items in the set, compared to the parental population and its stratification, which ensures the validity of the survey and makes it possible to judge the reliability of the information obtained (De Vaus, 2014); whereas, in the interview, the relevance of the information collected face-to-face depends on the quality of the interviewees. This is how we opted for the survey method, through 28 questions asked, to have information that is as representative as possible of the population concerned. We also sought the interviews — consisting of 25 questions, lasting nearly 37 minutes — to verify the validity of the results obtained during the survey.

To this end, we surveyed 312 companies spread over the majority of regions in Morocco, especially the biggest five containing the majority of Moroccan companies (Rabat—Sale—Kenitra; Casablanca—Settat; Marrakech—Safi; Souss—Massa; Tangier—Tetouan—Al Hoceima). The survey was conducted by the self-administration method: the respondent answers the questionnaire alone. This survey is descriptive in nature. Its main function is to describe the situation studied and to meet our need for information about barriers threatening digital investments. By opting for a descriptive survey, we favoured the instantaneous cross-sectional approach, which provides a snapshot of a situation studied at a given moment, over the longitudinal approach, which consists of conducting a survey periodically (Fowler, 2014). Admittedly, the latter is more exhaustive but requires fairly significant resources.

The sample was drawn from the Kompass database of 53,585 Moroccan companies. The targeted companies were classified according to the double criterion of the revenue and the number of employees, by reference to the regulatory arrangements about company size. Thus, in this survey, very small and medium-sized enterprises (SMEs) are those with a turnover of less than MAD 75 million and a workforce of fewer than 200 employees. Our survey covers the majority of companies in the national territory and targets all regulated companies, i.e., those with formal accounting. It concerns companies operating in the sectors of industry, construction, trade, and services and excludes from this field the financial, agricultural, and informal sectors. The survey was conducted between September and December 2022.

To build our mini-population of study, which is a kind of faithful reduced model, we opted for the random method, which ensures that each element of the population has an equal chance of being drawn from the base survey population. Following the results of this survey, we interviewed 74 business leaders from the 312 companies previously surveyed to verify the

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smooth running of the survey and confirm the results. The questionnaire protocol in this phase corresponds to that previously used in the survey. The sample of these respondents is distributed in the five regions of Morocco as follows: Rabat—Sale—Kenitra, 28 interviewed; Casablanca—Settat, 11 interviewed; Marrakech—Safi, 9 interviewed; Souss—,Massa 9 interviewed; and also 9 interviewed in the region of Tangier—Tetouan—Al Hoceima. The average duration of each interview was 37 minutes. The interview protocol consists of alternating open and closed questions, and general and detailed questions on the themes asked during the survey.

The survey sample was designed according to a stratified random survey based on the criteria of the number of employees and the activity as stratification variables. Its size ensures the required representativeness by sector of activity and by category of companies. It is drawn from the statistical directory of the Kompass database. The survey was initially addressed to 2,101 units: 769 representing industry, 371 construction, 294 trade, and 667 non-financial market services. Only 312 of the answers were confirmed and usable after three relaunches to obtain answers.

In addition, our sample includes different age groups of organizations with the predominance of companies in operation for 10 to 19 years (58%), and those with more than 20 years of seniority represent 32% of the sample. In terms of the industries of the sample studied, Figure 1 summarizes the distribution.

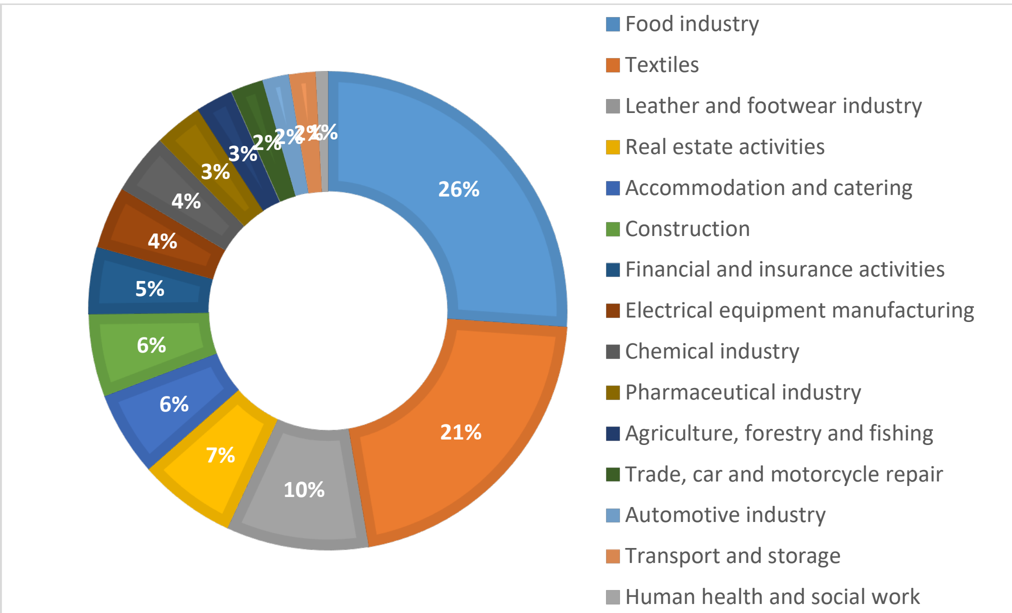

Figure 1. Industry breakdown (Source: authors from a field survey)

The survey required the mobilization of a collection staff of 8 people. It was carried out using the CAPI (Computer Assisted Personal Interviewing) collection method through a questionnaire that is based on a computer application that allows for the input, control, and electronic transfer of the data collected.

The representativeness of our sample is justified by the following formula:

$n = N/(1+N*e^2)$, where N = 53585, and e = 0.05 at 95% confidence level.

In our case, the sample size must be $n = \frac{53585}{1+(53585*(0.05)\wedge 2)} = 385$.

At the start of the survey, we attempted to approach 385 companies to respect this criterion of significance in relation to the size of the parent population. However, taking into account the conditions and procedure for carrying out the survey, we were only able to receive and conclusively process the responses from 312 companies, among which we had a sample of 74 companies to conduct an interview.

In this methodological approach of an exploratory nature, the information obtained from 312 companies from a survey, and 74 from an interview, made it possible to guarantee a significant representativeness of the study sample estimated at 53,585 companies registered in the Kompass database. Data processing was carried out via a combination of SPSS and Excel for better visibility and analysis of our data.

This methodological approach allowed us to have global visibility of the answers to the main questions of our research, and, above all, to bring out certain avenues of reflection and research on more specific questions dealing with obstacles to digital transformation. The presentation of this survey, its results, and its analysis will be described in the following section.

Results and Discussion

To understand the obstacles that threaten the digital transformation project in the Moroccan context, in this section, we analyze the results of our survey. This analysis will subsequently make it possible to compare these results with those obtained from the MIT study (Kane *et al.*, 2015), and the recent study on Europe (European Investment Bank, 2022), thus enabling a portrait of Morocco's positioning in terms of predisposition to digital transformation compared to the countries studied in these two reference studies.

Our survey attempts to highlight the main obstacles to digital transformation, starting first with the effect of the digital strategy. In the literature review above, several authors have noted the need for companies to implement a digital strategy through the creation of a common frame of reference for the different actions: a global and coherent vision that would link the different professions and actors. It is at this first point, relating to the availability of a clear and adequate digital strategy, that the respondents were questioned, and their results are summarized in Figure 2.

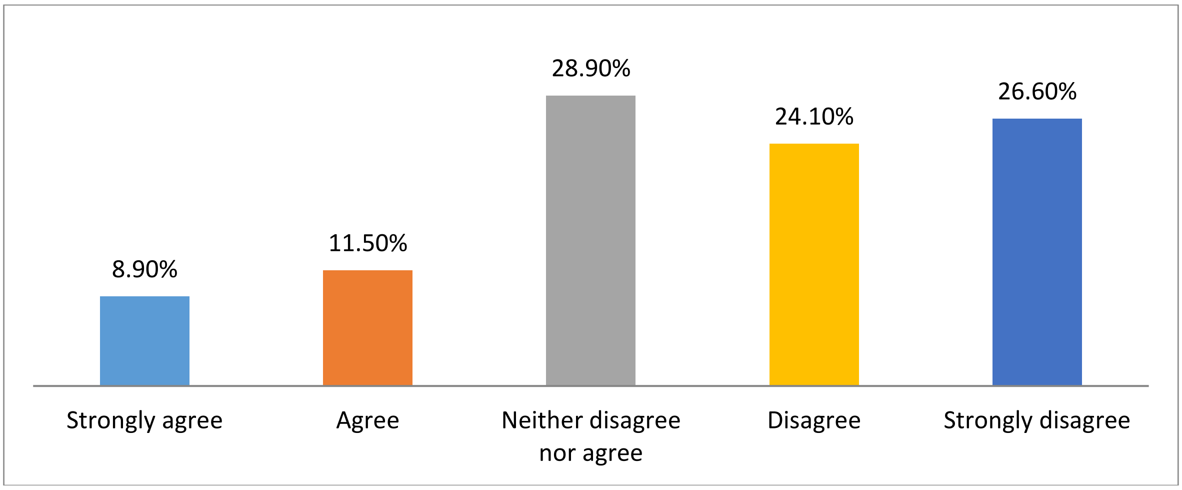

Figure 2. Availability of a clear and adequate digital strategy in the company

Analysis of the graph highlights that almost 50% of respondents disagree with the existence of a clear and adequate digital strategy in their company. This shows the real handicap of the digital strategy for the majority of Moroccan companies. What emerges from this survey is that more than half of the respondents underestimate their companies when discussing a digital strategy: what they leave unsaid is as if "*you have to be a multinational to talk about strategy*".

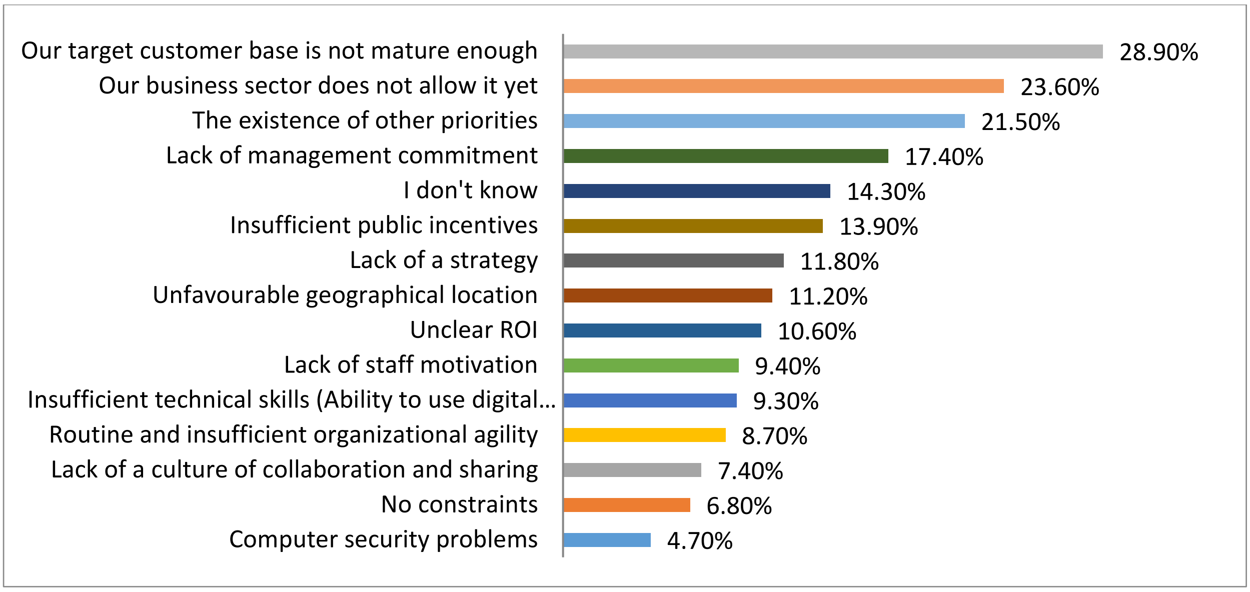

Figure 3. Roadblocks to digital transition

The complexity of the transformation process is perceived as the main obstacle to the digital transformation of Moroccan companies in our sample. Indeed, one-half of the people questioned say that the commitment to this evolution is discouraged by the complexity of the processes. These are essentially obstacles related to the immaturity of customers for business transformation (28.9%) and the level of evolution of the industry allowing this change (23.6%) – see Figure 3.

More than one-third of companies also consider that they do not have enough internal resources to face and implement the change necessary for digital transformation. This lack of skills is often linked to a lack of time, training, and motivation of internal teams, or a lack of sourcing to obtain specific external expertise.

The lack of leadership involvement is clearly characterized in Figure 4. More than 8 out of 10 respondents say they do not have a person or department responsible for the implementation and development of digital.

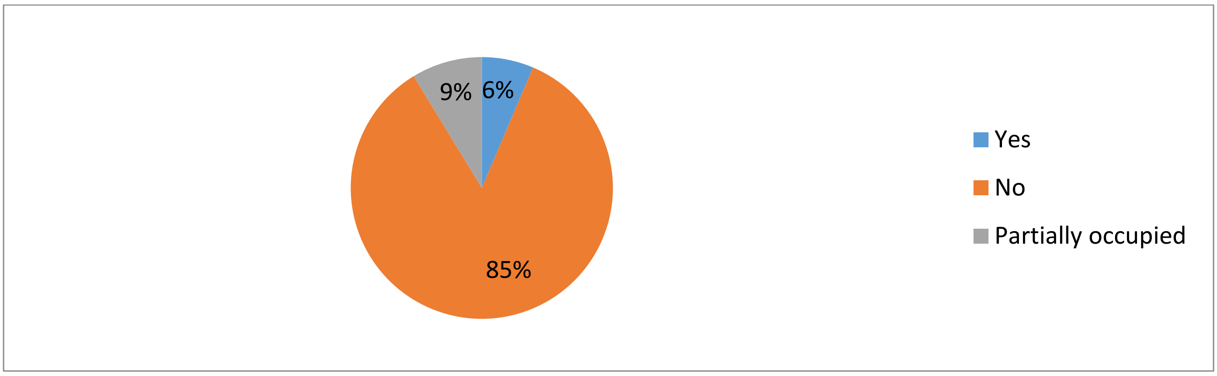

Figure 4. The responsibility (a person or a department) for the implementation of the digital project within the company

However, according to an observation made during the literature review on the obstacles of digital transformation, it is difficult to set up a truly cross-functional project for the company, with a global vision and a roadmap involving all the teams and all departments, without having the overall consistency of the transformation project demonstrated by a person leading this project. In this sense, the absence of a leader/responsibility for the digital transformation will lead to limitations in terms of the compatibility between the digital transformation strategy and the organizational strategy, which will surely limit the outputs of the digital transformation of the Moroccan companies. Among the 15% of companies that have defined a person responsible for the implementation of digital transformation, 35.8% of them are a department director, while 24.8% are generally heads of service, followed by a project manager (18.4%) and secretary general/Director General (12.3%).

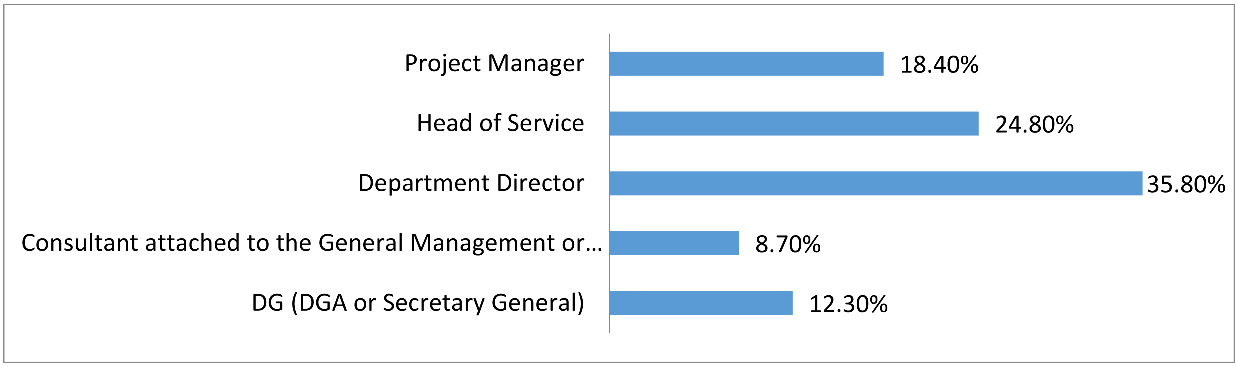

Figure 5. The highest position of the person responsible for the DT project

This lack of leadership to embody this change and carry it forward is also evident in the delegation of the digital strategy to the hierarchical levels of the organization chart of the company (Figure 5). This finding confirms previous studies claiming that, too often, digital

http://doi.org/10.18080/jtde.v12n1.814

transformation is mistakenly seen by leaders as a technological integration. If the general management is not convinced of the involvement of the entire company and does not embark on the project, it will never move forward despite individual or even collective goodwill within a department.

For one-quarter of companies, the return on investment (ROI) is a determining factor for digital transformation: companies take into account the return on investment of digitalization and what it will bring them in relation to the resources invested, even if it remains difficult to demonstrate the financial benefits of digital transformation.

Regarding security, the latter remains, for 30% of companies, an obstacle to digital transformation. In concrete terms, only 5% of companies have set up a real security governance organization. This confirms a lack of interest in the benefits that security management brings to the company: risk reduction, improvement in the quality of services, customer confidence, and competitive differentiation.

Based on the results of the analysis of the survey conducted, we can conclude that the digital transformation of companies in Morocco is still in the development phase, and not mature enough compared to the benchmark studied by Kane *et al.* (2015).

Indeed, the obvious delay in responding to interviews is also amplified by the lack of commitment from the State. One in three respondents declares that the lack of public incentives is one of the three determining factors of the non-digital transformation, alongside resistance to change and the immaturity of the context (customers and industry).

These findings relating to the case of Moroccan companies are largely in line with the results obtained by the study conducted in Europe (European Investment Bank, 2022), as well as that of Kane *et al.* (2015). All companies wishing or considering a digital transformation suffer from the same obstacles that we can summarize in 7 types of persistent obstacles: lack of internal resources and skills; Resistance to change; Return on investment not at all clear; Lack of leadership; The overall inconsistency of the transformation project; Cybersecurity Management; and Process Complexity.

However, there is therefore no difference in the nature of the barriers between countries, only in the degree and proportions of each factor constraining digital transformation.

Conclusion

Since the outbreak of the Covid crisis in 2020, digital transformation has become a central concern for any organization, as well as an ever-expanding field of research. Nevertheless, the emergence of this new societal paradigm still encounters difficulties in its proper implementation, mainly due to the existence of multiple obstacles.

Our study, based on a survey of 312 Moroccan companies and 74 interviews, has made it possible to determine the major obstacles to digital transformation. These are essentially the strategic and procedural complexity of the project, the lack of internal resources and skills, resistance to change and lack of managerial leadership, insufficient return on investment, security problems, and inconsistency of the transformation project.

This observation confirms the results obtained by other studies on the same theme, but in other jurisdictions: the obstacles are the same but their degree and their proportion change according to the level of digital development of the country.

Indeed, almost all companies, around the world are convinced of the interest and the need for their digital transformation. But they know that the path will be long and difficult, especially if they have neither the experience nor the culture of change. If the key success factors of digital transformation are known, the brakes too must be eliminated. This requires ambition, pragmatism, and a lot of commitment.

Theoretical contributions

Our work synthesizes the existing literature relating to the obstacles to digital transition. It enriches the current literature by addressing the digital barriers at the organizational level in one of the countries of the southern hemisphere, while the majority of other works consider the obstacles in the companies of industrialized countries or in a macro way, namely by relation to the economy as a whole. Additionally, our work presents an integrative approach to synthesizing the major barriers faced by organizations during their digital project. Therefore, our work can serve as a literature review basis for future works. Our article is also part of the current work initiated by Hillary (2004) and Diener & Špaček (2021) for more in-depth research and empirical studies related to the limits of the digital transition.

Managerial and technological implications

Many companies have defined a digital transformation strategy, but few are aware of the importance of what is at stake. The managerial interest of this research is to highlight the obstacles that hinder the implementation of the digital transformation project to be able to reflect effectively on the means of overcoming them. Thus, our work can serve as a guide for companies willing to start their digital journey, or those who have already started their digital road.

Limitations and future perspectives

Despite the representativeness of our sample, the main limitation of our study lies in the sampling. If not for a lack of resources to conduct a larger and more segmented survey, it

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would have been preferable for the sample size to be more representative than the 312 used in this survey, and above all for it to be analyzed by type of industry, technological maturity, and company size.

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Influence of ICT and Household Assets in the Penetration of Digital Economy in Mexico

An Empirical Analysis

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Abstract: The objective of this study is to validate the progress in the penetration of the digital economy in Mexico, between 2018 and 2022, from a composite index of household wealth based on microdata from a national telecommunications survey. An index of economic situation at the household level allowed us to measure that economic inequality persists between poor and rich households. Also, probabilistic regression models were used to validate the relationship between household wealth and digital economy participation. The models showed the gap remained practically at the same level between the two years; 26% in favour of the richest households. Educational level, age and experience in using the Internet were confirmed as the main differentiators in the condition of participation in the digital economy. The lack of progress observed in this research raises alarm bells about the lag of the poorest households in the productive use of the Internet and in the scope of its potential benefits. The digital issue should be included in the national political agenda, due to its scope in social, economic and social cohesion terms, along with other national problems, such as poverty, employment or well-being.

Keywords: digital economy, quantile regression, probit, household ICT wealth index, ENDUTIH.

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Introduction

At a global level, information and communications technologies (ICTs) are tools that enable rights to information, free expression, public participation, education, better health services and, ultimately, to be able to access a better quality of life. Furthermore, in different latitudes it has been found they can accelerate economic growth and positively impact productivity and employment (Ben Abdallah *et al.*, 2023; Katz, 2012; Pradhan, 2018). Therefore, at an aggregate level, interesting results are shown both in the aspect of telecommunications infrastructure and in their economic effect.

The pandemic accelerated the transition process towards the digital economy, since confinement forced people to use food delivery platforms, private transportation, and online buying and selling services, such as Amazon, AliExpress, eBay, Shopify, Uber and Rappi (CEPAL, 2023). It also encouraged the use of online financial services to carry out transactions, invest in financial or virtual assets, and so forth. According to official statistics from Mexico (ENDUTIH-INEGI, 2023) the percentage of people between 15 and 74 years old that used mobile banking services increased from 18.3% in 2018 to 23.3% in 2022, while people who carried out electronic commerce transactions increased from 18.2% to 43.9%. However, the literature that addresses the issue of the benefits of the digital economy from the demand side is scarce.

In such a context, the focus of this document is to fill a gap in the literature of the relationship between household assets and the digital economy. The validation of the relationship between these two variables is essayed to contribute a different scope. A strong assumption is that satisfaction with home, ICT and housing conditions positively influence the participation of people in the digital economy. The main background of this proposal is based on a study from India (Filmer & Pritchett, 2001) which accounted for the relevance of household asset variables. This research was done to describe the phenomenon of school access at a national or subnational governmental level, with the idea that complex phenomena in society can be explained with variables other than income or expenditure.

In microeconomic language, the principle of maximum utility (measured as satisfaction) is adopted, whereby more is better (Varian, 2010). In this research the reasoning is remarkably similar to that used in Varian's book, using 17 different variables to represent the welfare of the households (10 ICT assets and seven which represent household conditions habitability). Two editions of a national telecommunications survey, 2018 and 2022 (ENDUTIH-INEGI, 2023), are used to approximate progress in the use of the digital economy and account for inequalities in its use. A method is proposed to estimate digital gaps between households, based on socioeconomic variables. The sample is restricted to people between 15 and 74 years old.

Along with the implementation of a household wealth index to relate it to the digital economy, there is an absence of information on income or expenses. Consequently, the index is an input to measure the progress of the digital economy and inequalities in groups of households, according to their assets status. Therefore, said household wealth index is constructed and validated in two separate moments, 2018 and 2022, as an exercise that allows filling a gap on the issue of the digital economy in Mexico.

This article is structured as follows: the first section presents a review of the literature on the concept of digital economy and research for Mexico. Subsequently, the topic of advancement of digitalisation in Mexico is addressed, highlighting the main barriers to digital transformation. The fourth section presents the methodology, the work scheme and the variables used, both in the construction of the composite household index and in the probabilistic regression model by quantiles. Section five presents the results and their interpretation, as well as a sensitivity analysis. Subsequently, discussion sections, theoretical contributions, reflections on public policies and limitations are presented. Conclusions, references and an appendix are included in the final part of this literature review.

Varying definitions exist of what is meant by digital economy and its estimated size. The pioneering study of Tapscott in 1996 (in Bukht & Heeks, 2017, p. 4) defined digital economy as: "an economy based on digital technologies". However, Brynjolfsson & Kahin's (in Bukht & Heeks, 2017, p. 5) statement is more precise: "[it] refers specifically to the recent and still unrealised transformation of all sectors of the economy through the digitisation of information using computers." Nowadays, contemporary trends for the industry are reported (Groombridge, 2023). These represent new leading technologies in the industry such as digital immune system, applied observability, industrial cloud platforms, platform engineering, super applications, adaptive AI, metaverse and sustainable technology, among others.

According to the literature review, the relevance of the digital economy for a country seems clear, in terms of: i) new ways of production and distribution of goods and services (manufacturing, robotics, medicine, biochemistry, economics); ii) its impact on employment – valorisation and remuneration – of skills in more competitive markets; iii) its high added value, considering the amounts of capital and investment necessary for research and innovation; iv) institutional factors, such as the elements that allow for a smoother and more precise economic and social transition; and v) its contribution to aggregate income and general well-being.

From an academic and scientific perspective, it has not been an easy task to reconcile the economic, technological and social impact aspects of the use of technology. For instance, there is a reduced amount of research accounting for the economic impact of the digital economy in Mexico. The aggregate data on electronic commerce in Mexico is encouraging: it increased from representing 3.3% of the national GDP in 2013 to 5% in 2021; more than USD66 billion (INEGI, 2023a). Digitalisation attracts positive expectations in the short and medium term; that is, the COVID-19 pandemic accelerated the use of the Internet and telecommunications networks for different academic, work and, in general, daily life activities globally.

The last perspective, the use of technology and its implications, is significantly more studied in Mexico; however, there have been few studies of the implications of COVID-19 in economic or social terms. The prevailing outcome is the digital transformation of the country with a rapid transition – although with obstacles – towards digital practice in education, health, interaction with the government, organisational aspects and, above all, in employment and the way of doing business. Thus, this study focuses a magnifying glass on inequalities in the specialised use of the Internet for online banking or electronic commerce activities.

The main antecedent of this proposal are studies that were carried out in India. Filmer & Pritchett (1999, 2001) constructed a household wealth index (at the level of countries and subnational governments) to validate its effect on school achievement. Their main findings were that a wealth index is a consistent and robust predictor as much or more than economic income or expenditure variables when studying social phenomena related to health or education. The proposal by Filmer & Pritchett (1999; 2001) of the composite index presented: i) internal consistency; ii) robustness; iii) comparison between territories; and iv) alternative interpretations .

In Mexico, a precedent for the use of household goods and services in studies on economic progress and economic inequality took place in the Espinosa Yglesias Studies Centre (Monroy & Vélez, 2023, p. 88). This group of researchers used a methodology to account for the disadvantaged conditions of the population to determine the social mobility of people through a household economic resources index (a list of 14 goods and services), with the purpose of overcoming inequalities and achieving a more equitable state in Nuevo Leon. In the same vein, the composed index proposed in this document combines methodologies implemented in other research (Ovando & Olivera, 2018; Rodríguez, 2019) in terms of measuring the variables that have an influence on the probabilities that households – or individuals – access, use and get the most out of the Internet tool. The assets – or satisfiers – are used from the perspective of minimum conditions to enable the individuals in the digital economy.

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No less important is the Sixth Article of the *Political Constitution of the United Mexican States* (EPN, 2014) which in 2013 enacted the universal right to access broadband Internet, with the objective of guaranteeing the inclusion of the whole population as a knowledge society through a universal policy of digital inclusion. However, by 2022 there remains a persistent barrier to the advancement of digitalisation among Mexican households. The main reasons for the obstacle are economic 57.2%, followed by disinterest 25.2%, and lack of skills 9.6% (IFT, 2023).

Digitalisation efforts to reduce the digital divide in Mexico date back more than two decades (Ovando & Olivera, 2018): in 2002, first through the National e-Mexico System, later with the access to digital services in public libraries via Bill and Melinda Gates, after that within the framework of the Telecommunications Reform of 2013, the initial goal of Internet was connectivity of 65,000 public places (schools, health centres, parks and government buildings), rescheduled to 150,000 in 2016 and 120,000 in 2017 (SCT, 2017c). At the beginning of 2010, Casanueva-Reguart & Pita (2010) documented failures in the objectives of reducing the digital divide, concluding that poverty is one of the most important obstacles. Montiel (2016) attributed it to the lack of network coverage, fibre optic installation, lack of service providers and competition to inequalities in areas, cities and regions of Mexico. In the same order, the compilation of different studies for Mexico (Galperín & Mariscal, 2016) emphasised the relationship between the Internet and poverty for Mexico, in the context of the difficulties of moving towards a knowledge society.

In these terms, the national context frames a scenario of difficulties in the transition to a digital economy; that is, a transformation of such magnitude does not suggest an effortless path or straightforward policy measures. This context gives rise to the present empirical exercise, to validate the advance of the digital economy from the perspective of Mexican households.

Methodology

Variables that represent wealth in household ICT assets and living conditions are used to analyse their influence on household participation in the digital economy. The methodology is based mainly on three similar investigations: i) a pioneer study for India (Filmer & Pritchett, 2001) at the country level to analyse their relationship with educational attainment and educational enrolment; ii) a study for Mexico (Ovando & Olivera, 2018) focused on analysing the influence of household wealth on the adoption of the Internet, within the framework of the Telecommunications Reform of 2013; and iii) a study for Mexico (Rodríguez, 2019) where an ICT asset index was built to explain the determinants of adoption and use of the Internet in Mexico.

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Based on the above, this paper fills a gap by doing an analysis by quantiles, comparing two different moments, pre- and post-COVID-19 pandemic (2018 and 2022). A household wealth index is constructed using the method of principal components (or PCA) and home conditions with two types of variables: ICT and home. A programming code STATA V17 was built in the statistical and econometric software.

The ENDUTIH survey (National Survey on Availability and Use of Information Technologies in Households) was used for both years. This survey has been carried out annually and systematically since 2015 in Mexico, with representation at the national, state, urban and rural levels and of cities. Previous instruments were MONACO (National Computing Module) 2002–2023, and MODUTIH (Module on Availability and Use of Information Technologies in Households) from 2004 to 2014. Information about income or expenses is not captured. So, variables of telecommunications assets and services were used, which allowed us to approximate the level of "wealth" of households in the long term.

Data

2018 (n = 76098)	**2022 (n = 38027)**

Dependent variable: digital economy participation
(e-commerce use | e-banking use)

Independent variables

Variables of household ICT services and assets: radio, analog TV, digital TV, videogames console, mobile cell phone, computer, tablet, Internet service, pay TV service, fixed telephony, monthly spending in ICT services[1]

Housing variables: no dirt floor, underground water, drainage, refrigerator, washing machine, motor vehicle

Analysis by quintiles

Construction of household wealth indices (ICT and non-ICT) PCA method

Probit model: quintile regression analysis

$$Digital\ economy_{t=2018,2022}(HQ, X)$$

$$Digital\ economy = \left\{\frac{1 = participation}{0 = no\ participation}\right\}$$

HQ = Household wealth by quintile: poorest, middle and, richest

X = Household and personal variables

Economic status index estimation

Probit model

Figure 1. Research framework

Notes: The amount was calculated based on the household's monthly spending on telecommunications services. The conversion from Mexican pesos to US dollars was carried out for both years based on the average value of the year: 19.24 Mexican pesos per USD in 2018 and 20.12 for the year 2022.

The indices for both years are used to validate their influence on the advancement of the digital economy in Mexico, through electronic commerce or online banking activities by a representative individual of households. Figure 1 presents the most important aspects of the scheme that this research followed.

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It should be clear that the household wealth indices constructed for the years 2018 and 2022 do not reflect levels of well-being but are used to relate them to participation in the digital economy. The idea behind domestically owned ICT assets is that they are held mainly for practical and useful reasons, not contemplative ones. The reason is that they are means that facilitate everyday activities such as obtaining valuable information, comparing prices and the quality of goods and services, saving time in transactions, reducing costs and definitely increasing consumer surplus, which is obtained when carrying out online banking or electronic commerce activities. Typically, consumer spending patterns have been used as an indicator to measure poverty in households. However, national surveys also provide a wealth of data that is very useful for econometric purposes (Deaton, 1997; Montgomery *et al.*, 2000).

In practical terms, using ICT assets carry conceptual and empirical limitations that cannot be attributed to the asset index. The major problem of grouping ICT household assets is: i) it is not done with any distinction between them (for example, allocating each different weights); ii) some of them do not embody the idea of being critical technology or even useful for all members of the household (for example, having a video game console); and iii) it is supposed that more ICT assets are better, in terms of their utility. This last assumption is overcome considering that the goods are consumed or possessed for non-contemplative purposes; for instance, for school or work purposes as a way to increase knowledge and skills, or simply for entertainment.

Regarding the use of the principal components method and microdata, a greater amount of information is used (Galperín & Mariscal, 2016; Martínez-Domínguez, 2020) by reducing external validity (due to the size of the sample). Allowing plausible assertions and methodologically sound assertions, there are lower levels of aggregation and they are usually representative, instead of using individual variables to explain economic performance, such as broadband (Castaldo *et al.*, 2018; Díaz *et al.*, 2016; Koutroumpis, 2009; Qiang *et al.*, 2009).

Also, at the end of this the document, a sensitivity analysis section is included to account for the consistency and robustness of the results: first, through a reduction of variables used to construct the household wealth index and second, through the use of parsimonious specification models, using only the variables of greater effect.

Variables and Data Used to Approximate Household Wealth

Given that digital economy insertion is examined, the sample was restricted to individuals who used the Internet in the last three months in two economic main digital activities: e-commerce and/or e-banking. Different from other studies and approaches, the household's information was captured because the goal of this study is to elucidate the economic and social pressure inside the family as a whole, not only from one specific person. Sample sizes were 76.098 and

38.027 for the 2018 and 2022 surveys, respectively (see Table 1 where the information is presented according to the condition of participation in the digital economy of households).

Table 1. Descriptive statistics by condition of participation in digital economy, 2018 and 2022

Year / Statistics / Household variables	2018						2022					
	observat-ions (in millions)		Mean		Standard deviation		Observat-ions (in millions)		Mean		Standard deviation	
	DE use	Non-DE use	DE use	Non-DE use	DE use	Non-DE use	DE use	Non-DE use	DE use	Non-DE use	DE use	Non-DE use
Radio	3.5	7.2	0.575	0.573	0.494	0.495	5.1	6.6	0.461	0.487	0.498	0.5
Analog TV	2	5.2	0.333	0.413	0.471	0.492	1.8	3.3	0.168	0.239	0.374	0.427
Digital TV	5.2	9.5	0.857	0.755	0.35	0.43	9.8	10.9	0.895	0.797	0.306	0.402
Video games console	1.7	1.6	0.278	0.125	0.448	0.331	2.9	1.4	0.263	0.105	0.44	0.306
Mobile cell	6.1	12.4	0.992	0.981	0.088	0.136	11	13.5	0.996	0.99	0.063	0.099
Computer	4.5	5.7	0.729	0.451	0.445	0.498	7.4	4.8	0.669	0.355	0.471	0.478
Tablet	2.5	2.9	0.413	0.228	0.492	0.42	3	1.7	0.275	0.121	0.446	0.327
Internet service	5.2	8.3	0.854	0.656	0.354	0.475	9.9	10	0.9	0.734	0.301	0.442
Pay TV service	3.7	6.5	0.61	0.512	0.488	0.5	5.4	5.7	0.491	0.415	0.5	0.493
Fixed telephony	3.4	5.2	0.562	0.412	0.496	0.492	5.8	5	0.525	0.369	0.499	0.482
No dirt floor	6.1	12.4	0.995	0.981	0.072	0.135	10.9	13.3	0.989	0.973	0.102	0.162
Underground water	5.7	10.1	0.927	0.796	0.259	0.403	10.1	10.5	0.915	0.772	0.279	0.419
Drainage	5.5	10.4	0.903	0.82	0.295	0.384	9.7	10.7	0.884	0.786	0.321	0.41
Refrigerator	5.9	11.6	0.97	0.915	0.171	0.279	10.6	12.4	0.964	0.906	0.185	0.291
Washing machine	5.3	9.9	0.871	0.783	0.335	0.412	9.6	10.5	0.875	0.768	0.33	0.422
Motor vehicle	4.2	6.1	0.683	0.485	0.465	0.5	7.1	6.1	0.642	0.448	0.479	0.497

Source: Prepared by the authors.
Notes: In 2018, there were 60,74 million people in 18,77 million homes. In 2022, there were 76,86 million people in 24,63 million homes. Information captured in the household questionnaire among informants between 15 and 74 years of age. DE use/ Non-DE use: participation and non-participation in digital economy. The average monthly spending amount for telecommunications services is presented in the Appendix (Figure A1).

Eleven out of 17 variables are related to the possession of telecommunications assets or services (radio, analog TV, digital TV, video games console, mobile cells, computers, tablets, Internet service, pay TV service and fixed telephony). They take values of 0 and 1 and represent one of the average monthly spending on ICT services. Whereas three of them account for the physical conditions of the house (no dirt floor, piped water and drainage), and three account for possession of durable household goods (refrigerator, washing machine and vehicle).

A first review allows us to observe some progress in the availability of ICT satisfaction between the two groups; between those who participated and those who did not participate in the digital economy. Likewise, that there is less disparity in home amenities, such as basic drainage services, refrigerator or washing machine, was considered.

http://doi.org/10.18080/jtde.v12n1.876

The household was used as the unit of analysis and some information was recovered from another three questionnaires related to residents, users and housing conditions. In this survey, the information collected is from a key informant in the household, so the perspective is from the inhabitant's own experience and not from the perspective of all household members. The information was collected in the second quarter of the respective years.

In the next section, an economic index of households using principal components analysis is presented. The grouping of households into three quantiles (poorest 40%, middle 40% and, richest 20%) was defined, based on official data on the percentage of millions of people living in poverty in Mexico, which ranged from 41.9% to 36.3% between 2018 and 2022 (CONEVAL, 2023). The definition of poverty involves the percentage of the population whose income is less than the value of the well-being line and that suffer from at least one social deficiency in education, access to health services, access to social security, quality and spaces of housing, access to basic services in housing, and access to food.

Economic status index of households

In the Appendix (Table A1 and Table A2), the scoring factors of the first component of the PCA methodology of the selected variables are reported. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy takes values between 0 and 1, and values above 0.5 are considered satisfactory for a PCA. For 2018, KMO=0.8012, and for 2022 KMO=0.7658. The component loadings for PC1 and PC2 are presented in Figure A2 and Figure A3, where the first component contributed 22.23% and 22.05%, for each of the years 2018 and 2022. Households were ordered by their wealth index into three categories: poorest (40%), middle (40%) and richest (20%).

For 2018, the average value of the index is 0; the standard deviation is 1.94. Due to all of the set variables (except the availability of monthly payment in digital services) taking only the values 0 or 1, the weights are easily interpreted. A movement from 0 to 1 changes the index in terms of a derivative, which is the change in the variable when going from 0 to 1. Dividing the scoring factor by the standard deviation ($f1i/s^*i$) would mean an increase in the asset index; for example, a household that has Internet service has an asset index 0.77 higher than one that does not have it. Owning a computer increases a household's asset index by 0.66 units; the values make sense, since – in the opposite direction – having an analog TV (after the 2013 Telecommunications Reform, a public policy was implemented and digital televisions were granted to carry out the analog blackout and transition to digital television) reduces the asset index by 0.15.

The difference between a rich household and a middle one is 1.69 units and between a rich one and a poor one is 4.43 units. An example of a combination of assets that a household among

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the richest (top 20%) and not a household among the poorest (bottom 40%) would possess would be the condition of: owning a digital television (0.57), having a computer (0.66), a tablet (0.51), Internet service (0.77), home drainage system (0.51), washing machine (0.68) and a vehicle (0.58). The highest differences are present in ICT assets, like a tablet, Internet service or video games console, whereby in household goods, it is clearer through ownership of a vehicle.

The difference in points between the poorest group and the richest group is 4.40 units. One combination of assets that would make such a difference would be owning a cell phone, a computer, Internet service and a vehicle. As in the results of 2018, the difference between owning and not owning telecommunications assets and other goods used in the home would be maintained; that is, the value calculated in both years is remarkably similar and therefore the backlog of satisfaction would remain.

Taking into account the pressure for poorer households, the average household expenditure on fixed telecommunications from 2010 to 2014 (IFT, 2016) of the first decile with respect to their income, was reduced from 15.5% to 10%. However, a percentage still much higher than that allocated by households from the 10th decile in 2014 was 1.8%. Likewise, as a way of approximating such differences, the data of the year 2022 (ENDUTIH-INEGI, 2023) an average monthly expenditure of USD 17.5 was obtained, a reduction of 8.9% with respect to the year 2018 (ENDUTIH-INEGI, 2018). In Mexico the prices of the devices and of telecommunication services have been considerably reduced since the ends of previous presidential regimes since 2013 and it also helped the implementation of the public policy Mexico Connected (SCT, 2017a) through Internet access services in granted public sites and training and digital education. It sought to reduce the digital divide existing in the country, which prevents the free exercise of the constitutional right previously established in Article 6 of the Constitution.

For 2022, the quantitative variable of average monthly spending on digital services also sheds light on the differences between the groups; a rich household (decile 10) spends, in USD dollars, 22.5 times the amount of the poorest 10% of households, USD40.86 versus USD1.82 (Figure A1); a value that increased in respect of the 2018 data, to a value of 16.4 times, USD44.4 versus USD2.71.

Continuing with this scenario, the next section presents the results of the regression analysis by quantiles.

http://doi.org/10.18080/jtde.v12n1.876

The probit model

Due to the nature of the values of the dependent variable, a value of 1 is assigned if the household is integrated into the digital economy (use of electronic commerce or online banking) and 0 otherwise, and the effect of each explanatory variable on the dependent variable is approximated by a non-linear curve. Categorical variables are included in order to differentiate between groups of households.

In terms of the model, it adopts the following expression for each of the years 2018 and 2022, separately:

$$E(Y_i|X_i) = \beta_0 + \beta_i X_i$$

where $E(Yi|Xi)$ indicates the probability that the home has Internet, given certain characteristics or values that each independent variable takes, that is, Pi = Probability that Yi=1 y 1-Pi = Probability that the household does not participate in the digital economy. Xi = each of the independent variables that affects the probability that a home has Internet or not. That is, Yi follows the Bernoulli distribution (Gujarati & Porter, 2010). That is, the conditional expectation is interpreted as the conditional probability of Y_i

$$E(Y_i|X_i) = \beta_0 + \beta_i X_i = P_i$$

Or, in terms of probabilities, it would be equal to the probability of success divided by the total probability (success plus non-success). For the total model:

$$\begin{aligned} Prob(Dig\_Eco = 1) \\ &= \Phi(\beta_0 + \beta_1 * Sex_i + \beta_2 * Sq_{age_i} + \beta_3 * HQ_i + \beta_4 * Time_{Internet-user_i} + \beta_5 * Age_{group_i} \\ &+ \beta_6 * School_{attainm_i} + \beta_7 * Locat\_size_i + \beta_8 * Hou\_size_i) \end{aligned}$$

For the group models (separately), poorest (40%), middle (40%) and richest (20%):

$$\begin{aligned} Prob(Dig\_Eco = 1) \\ &= \Phi(\beta_0 + \beta_1 * Sex_i + \beta_2 * Sq_{age_i} + \beta_3 * Time_{Internet-user_i} + \beta_4 * Age_{group_i} + \beta_5 \\ &* School_{attainm_i} + \beta_6 * Locat\_size_i + \beta_7 * Hou\_size_i) \end{aligned}$$

or seen in ratio terms:

$$Prob(Y|X) = \frac{\exp(\beta_0 + \beta_i X_i)}{[1 + \exp(\beta_0 + \beta_i X_i)]}.$$

to validate the effect of the determining variables on the probability of household participation in the digital economy. Table A3 presents the results for 2018 and 2022, with the purpose of comparing their differences and magnitudes.

http://doi.org/10.18080/jtde.v12n1.876

Regression Model Results

As has been confirmed in other studies, the variables related to educational level, geographical location, average household members and age group do not present a divergent pattern (Martínez-Domínguez, 2020; Rodríguez, 2019). Furthermore, this result highlights the importance of the experience as an Internet user. The magnitudes of the effects by groups do stand out.

Interpretation of parameters

Regarding the **Sex** variable, the negative and statistically significant value indicates that women would have a probability of participating in the digital economy that is 5.9% lower than the probability that a man would have. This gap would have been reduced 50% in 2022 with respect to the level of 2018.

When comparing the **wealth of ICT assets** between households by quintile, two compelling facts are observed that shed light not only on the process of transition to the digital economy as a whole, but also on the widening of gaps between households; for example, quintiles 2, 3 and 4 consistently increased the use gap with respect to the poorest household group. In the case of the richest households, the gap was practically maintained for four years (a probability of 26% higher than that of the group of poorest households, *ceteris paribus*). This tells us that despite the global increase in the use of the digital economy, the issue of inclusion in the use of a fundamental purpose of the Internet is not being met.

The results on the variable of length of **time as an Internet user** and its influence on the probability of participating in the digital economy *ceteris paribus* would indicate progress in reducing the gaps between the different groups of households; in all cases, even if marginally, the differences compared to people who have used the Internet for less time were reduced. An important fact is that the availability of mobile phones allows free Internet connectivity at different points, whether in schools, recreation centres, government offices or workplaces, as long as there is network infrastructure.

In **age groups**, it is found that the most dynamic one in the digital economy is the one aged between 25 and 34 years old whereby the gap appears with greater intensity when considering wealth in ICT assets. It is interesting to note that there is little difference between the youngest age groups 15–24 years and people over 45 years of age (the coefficients are not statistically significant, with the exception of the group richest in ICT assets). This finding would initially raise concern in the economy since the income of mature people is consistently higher. The earnings of adults are not only higher, but will increase with age, especially among the most trained or educated people.

http://doi.org/10.18080/jtde.v12n1.876

Consistent with the above, the results of the models indicate that the variable with the greatest weight in the digital economy is **educational achievement**. First, the values of the coefficients for 2022 are greater than those for 2018, which means that the gaps in participation in the digital economy widened with respect to those who had schooling up to primary school. Second, in 2022 a person with a high school education from a poor, middle or rich household would have doubled their probability of participating in the digital economy *ceteris paribus*, compared to the difference that existed four years before (14.8% versus 6.9%, 20% versus 10% and 23% versus 11%, respectively).

Regarding the **size of the locality**, the effect of the most urbanised areas on the most dispersed territories or with lower population density is confirmed, with few differences in the coefficients for both years.

The last variable, the **number of members of a household**, accounts for the indirect effect of economic pressure in a family; for example, more household expenses have a negative impact on integration into the digital economy, in other cases it may mean whether or not to send one of the children to school. The effects of COVID-19 posed different challenges among students, at all educational levels in Mexico, from the impossibility of having a computer to browse the Internet, to not having spaces at home to study. In all cases and in all groups, there is an inverse relationship between household size and its insertion into the digital economy.

In all models the value of Chi2 is statistically significant (less than 0.05), so the independent variables integrated in the models are capable of predicting the dependent variable. The classification accuracy of the observations and the number of correct predictions of the models in all cases was greater than 70%. Therefore, the model is considered adequate to explain the phenomenon.

In the next section, a sensitivity analysis is detailed.

Sensitivity analysis

To validate the consistency and robustness of the results both to measure the Economic Situation Index and to run the quantile regression models, two additional analyses were carried out for 2018 and 2022: i) a reduction in the number of variables used to build the index of ICT assets and minimum home habitability conditions; and ii) use of the principle of parsimony in the approach of functional forms, in which a smaller number of variables is chosen (in this case, taking into account the literature). The essence of this final exercise is to corroborate that the group of the poorest, in its relationship with participation in the digital economy, did not advance in participation in the digital economy between the two years analysed, 2018 and 2022.

http://doi.org/10.18080/jtde.v12n1.876

One of the main initial advantages of quantile regression models – at least with respect to linear regression models, or those that use ordinary least squares, OLS – is that different results can be obtained for the dependent variable (not an average for the entire sample). This is due to the “piecewise” regression that is done according to the classification of individuals – in this case households – of the entire sample (Porter, 2015).

Scenario 1: Reduction of the variables used in the quantile regression models

We decided to reduce the number of variables used to construct the household ICT wealth index (from 17 to 11) following criteria of little variability between groups, assets with a tendency to disuse or to leave only fictitious variables, so the omitted variables were: radio, analog TV, mobile telephony, landline telephony, average monthly spending on ICT services and no dirt floor. The results indicate the pattern found in the previous models in respect of the use of digital economy (Table A4) that: i) the digital gap between the poorest and the richest households increased from 26.9% to 29.6% between 2018 and 2022; and ii) the educational level was confirmed as the differentiating variable by registering increases of between 60% and 80% between the two years, especially when considering higher education levels among the three quantiles.

Scenario 2: Results considering parsimonious models

Parsimonious models were run; that is, restricting the use of variables to those recurrent in the literature, such as education level, sex, urban–rural and age group, in addition to the household wealth index variable in quantiles, using the 11 aforementioned variables. The main results (see Table A5 and Table A6) indicate: The digital gap in the use of the digital economy increased between the two years analysed: i) the gap between quintile 5 and 1 increased from 29.9% to 31.9%; and ii) at the educational level the gap increased, although slightly, between 2 and 6 percentage points.

It is worth mentioning that the variations in the fit of these models (when observing the values of the pseudo R squared), with respect to the previous one, are marginal, so the results appear consistent, even when the number of predictors was reduced.

Discussion

The objective of this work allows us to affirm that, at the household level, digital gaps persist when specialised use of the Internet is analysed. Although progress has been made in the percentage increases in household asset ownership, gaps persist in asset wealth indices, which is presumed to hinder the advancement of the digital economy in general. The quantile regression analysis, in turn, allows us to identify that the variables with the greatest effect on the probability of using the Internet in the digital economy remain educational level, experience in using the Internet (which implies digital literacy), the place of residence and the age group. In this regard, at government level, efforts have been implemented for digital inclusion, such as the new National Digital Strategy (under the motto of "Leave no one behind") (EDN, 2021). Another implementation of that project was to supply the Internet at an affordable price and of quality, especially to locations with less coverage and use of the Internet network (CFE, 2023) and the Connected Mexico Points (SCT, 2017b).

Theoretical contributions

This paper provides several theoretical contributions: trying a different methodology from traditional ones; exploring what variables other than income or expenditure are capable of explaining a complex phenomenon such as participation in the digital economy; the use of microdata from a national survey to build an economic status index based on household assets, approximating their economic and social situation; to be interdisciplinary in academia and science, by addressing economic, social and demographic aspects of a cross-cutting issue, such as the use of technology and the possibility of influencing national digital policy; and the possibility of coinciding with other similar works, such as the Digital Economy and Society Index, DESI (EU-EC, 2023), which is prepared for European countries and attends social and economic aspects of the use of technology. With this work, an analysis of "digital" social mobility could also be prepared, recovering The Espinosa Yglesias Study Center (CEEY) approach.

The sensitivity analysis testing of two different scenarios made it possible to verify the persistence of the digital divide when comparing the poorest quintile with the richest. Also, the educational level remained the greatest differentiator between households. The results of the regressions by groups, in general, maintained the direction of the effects.

Reflections in terms of public policy

Households with less ICT wealth are less inserted in the digital economy; whether when considering the educational level, the distance from urban centres, the size of the home or the length of time in using the Internet tool. Thus, an opportunity exists to target subsidy programs for certain homes or populations far from urban centres, with active participation and coordination between the federation and local, state and municipal governments.

Educational policy, especially at basic levels, must be designed and implemented considering global trends in digitalisation. Mobile connectivity is also an area of opportunity for the use of the digital economy. The Connected Mexico Point Network was a worldwide award-winning project at WSIS 2017 (the World Summit on the Information Society Forum) (SCT, 2017b) as the best use case in the "Skills Development" category. It is an experience that must be resumed and renewed.

In the case of employment, around 55% of the population is found in the informal economy (INEGI, 2024). This fact inhibits potential advancements in digitalisation for a large part of the population from gaining access to the formal system (for instance, digital financial inclusion, appropriate use of credit, savings, and approach to investment instruments).

It is imperative to advance at an educational level as a determining variable in the take-off of the economy and, at the same time, to reduce the digital divide as a way to achieve greater digital inclusion of the Internet and associate it with digital literacy. This result addresses the risk predicted more than 20 years ago, in terms of the increasing gaps between those who do and do not have the Internet (Wresch, 1996) or when considering the specialised use of technology (Adeya, 2002).

Another approach is to set the issue of reducing inequalities in Mexico at the core. The Gini coefficient in Mexico is one of the highest not only in the Latin American & Caribbean countries , but in the world, for example, it is the second most unequal country among OECD countries, 45,4 (World Bank, 2022). These disparities are reflected and maintained when talking about the digital issue.

Limitations and futures perspectives

The main limitation to the study is that the instrument used did not collect information on household income or expenditure. The collected information was not from all members of the household but from a representative. The literature review was carried out mainly at the national level and, above all, on issues of digital divide and technological infrastructure (Escobar & Sámano, 2018). Another limitation is the analysis used: trying other models or with other aggregations should be tested to strengthen the arguments presented.

Another aspect that was not addressed in this work is how to exploit the issue of the contribution of the digital economy to the national economy, running an analysis at the level of the business ecosystem and its insertion into the digital economy, in a process of transition to digital transformation. An alternative would be the use of other official sources, such as the Economic Census (which is five-yearly) and the National Occupation and Employment Survey (ENOE-INEGI, 2023) which is quarterly, and which would allow the analysis of the Mexican business ecosystem, on the path of a digital transformation process.

These findings open the door to the possibility of measuring the concentration of human capital and skills, as attractive factors for companies, investments and technology. Or, on the

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other hand, of identifying vulnerabilities to overcome social lags and inequalities in different segments of the population.

Conclusions

The advancement of the digital economy is essential in Mexico. Its participation in GDP has increased in recent years. Mexico is a country of considerable heterogeneity in digital advancement but also in economic and social progress. The value of official statistics shows – both in percentage and in added value – the advancement of the digital economy. However, there are segments of the population on the margins of the information and knowledge society, in terms of using specialised Internet tools.

This work is focused on elucidating the advance of the digital economy in types of households, according to their wealth and based on two representative samples, pre- and post-COVID-19 pandemic, 2018 and 2022. The two main findings were: 1) the lack of progress in reducing household wealth gaps (a difference in favour of the richest households remained at 4.4 points, which translated into owning up to seven more assets or satisfiers in the rich household than in the poor one); and, 2) the persistence of inequality in participation in the digital economy between quintiles 1 and 5, a gap that remained 26% in favour of rich households over poor ones. The sensitivity analysis allowed us to corroborate the digital gap and the persistence of inequalities. Therefore, it is necessary to think about endowments when conducting an economic analysis (Milanovic, 2017).

Another outstanding fact is that the educational level was consolidated as the greatest differentiator in the probability of participating in the digital economy, which would indicate the need for policies and programs that result in digital literacy and the productive use of the Internet. The most recent results of the Programme for International Student Assessment (PISA) test are flags to the education sector at all levels that a national economic strategy needs implementation.

In Mexico, the transition towards an economy based on knowledge and technology is being perceived and worked upon. However, household conditions could be improved to accelerate the transition along this path. One of the dilemmas at the public policy level is to satisfy targeted policies to accelerate the digital economy.

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Appendix

Table A1. Comparison of scoring factors and summary statistics for selected variables entering in the computation of the principal component analysis, 2018

Variable/Stats	Mexico				Means		
	Scoring factors	Mean	Standard Deviation	Scoring factor/-Standard Deviation	Poorest 40%	Middle 40%	Richest 20%
Radio	0.094	0.554	0.497	0.189	0.477	0.544	0.726
Analog TV	-0.071	0.404	0.491	-0.145	0.477	0.387	0.294
Digital TV	0.233	0.786	0.41	0.568	0.593	0.876	0.99
Video games console	0.223	0.985	0.121	1.843	0.032	0.161	0.521
Mobile cell	0.083	0.985	0.121	0.686	0.97	0.993	0.998
Computer	0.33	0.556	0.497	0.664	0.2	0.704	0.968
Tablet	0.233	0.297	0.457	0.51	0.102	0.3	0.682
Internet service	0.34	0.737	0.44	0.772	0.396	0.947	0.999
Pay TV service	0.209	0.572	0.495	0.422	0.379	0.617	0.866
Fixed telephony	0.327	0.435	0.496	0.66	0.086	0.542	0.92
Average monthly spending in ICT services	0.368	19.15	16.75	0.022	7.18	21.86	37.69
No dirt floor	0.101	0.987	0.112	0.9	0.971	0.998	0.999
Underground water	0.257	0.875	0.331	0.777	0.717	0.972	0.997
Drainage	0.183	0.844	0.363	0.505	0.715	0.913	0.966
Refrigerator	0.226	0.943	0.232	0.975	0.862	0.996	1
Washing machine	0.263	0.814	0.389	0.675	0.618	0.921	0.991
Vehicle	0.285	0.575	0.494	0.577	0.296	0.672	0.941
Economic Status Index			**1.944**		**-1.979**	**0.756**	**2.447**

Source: prepared by the authors.
Note: Scoring factor is the "weight" assigned to each variable (normalised by its mean and standard deviation) in the linear combination of the variables that constitute the first principal component. The percentage of the covariance explained by the first principal component is 22.2%. The first eigenvalue is 3.78; the second eigenvalue is 1.38.

Table A2. Comparison of scoring factors and summary statistics for selected variables entering in the computation of the principal component analysis, 2022

Variable/Stats	Mexico				Means		
	Scoring factors	Mean	Standard Deviation	Scoring factor/-Standard Deviation	Poorest 40%	Middle 40%	Richest 20%
Radio	0.079	0.452	0.498	0.159	0.376	0.465	0.578
Analog TV	-0.078	0.223	0.416	-0.188	0.291	0.193	0.145
Digital TV	0.26	0.831	0.375	0.694	0.643	0.938	0.995
Video games console	0.215	0.164	0.37	0.581	0.026	0.138	0.492
Mobile cell	0.056	0.993	0.085	0.659	0.985	0.997	0.999
Computer	0.311	0.482	0.5	0.622	0.153	0.586	0.932
Tablet	0.206	0.187	0.39	0.528	0.049	0.167	0.505
Internet service	0.321	0.798	0.401	0.8	0.519	0.977	1.0
Pay TV service	0.217	0.463	0.499	0.435	0.252	0.506	0.799
Fixed telephony	0.328	0.393	0.488	0.672	0.058	0.483	0.884
Average monthly spending in ICT services	0.36	15.93	16.45	0.022	4.47	17.96	34.83
No dirt floor	0.108	0.982	0.133	0.809	0.961	0.995	0.998
Underground water	0.284	0.84	0.367	0.774	0.636	0.965	0.996
Drainage	0.209	0.785	0.411	0.509	0.613	0.872	0.955
Refrigerator	0.242	0.935	0.246	0.982	0.843	0.995	1

Variable/Stats	Mexico				Means		
	Scoring factors	Mean	Stan-dard Devia-tion	Scoring factor/-Standard Deviation	Poorest 40%	Middle 40%	Richest 20%
Washing machine	0.275	0.811	0.392	0.702	0.604	0.927	0.991
Vehicle	0.273	0.552	0.497	0.549	0.29	0.632	0.918
Economic Status Index			**1.936**		**-1.951**	**0.725**	**2.453**

Source: prepared by the authors.
Note: Scoring factor is the "weight" assigned to each variable (normalised by its mean and standard deviation) in the linear combination of the variables that constitute the first principal component. The percentage of the covariance explained by the first principal component is 22.1%. The first eigenvalue is 3.75; the second eigenvalue is 1.40.

Table A3. Marginal effects of wealth groups in the probability of participate in digital economy: probit regression results, 2018 and 2022

Variables/Year	Total		Poorest (40%)		Middle (40%)		Richest (20%)	
	2018	2022	2018	2022	2018	2022	2018	2022
Dependent variable: Digital economy participation								
Independent variables								
Sex = man (reference)	-0.059***	-0.029***	-0.039***	-0.009	-0.064***	-0.035***	-0.088***	-0.054***
Squared age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Households ICT asset wealth: quantile 1 (reference)								
Quantile 2	0.080***	0.101***						
Quantile 3	0.139***	0.154***						
Quantile 4	0.193***	0.201***						
Quantile 5	0.263***	0.260***						
Time as Internet user: less than one year/don't remember (reference)								
Between 1 and up to 2 years	0.012	0.006	0.011	0.025	0.027*	-0.026***	-0.065*	-0.039***
More than 2 and up to 5 years	0.067***	0.054	0.064***	0.064	0.078***	0.041	0.011	0.002**
More than 5 years	0.205***	0.171***	0.177***	0.176***	0.233***	0.166***	0.200***	0.146***
Age group: 15–24 years old (reference)								
25–34	0.044***	0.060***	0.011	0.007	0.062***	0.093***	0.095***	0.122***
35–44	-0.003	0.030***	-0.022	-0.024	-0.004	0.044**	0.047***	0.110***
45–54	-0.041***	0.001	-0.054**	-0.049	-0.039*	0.000	-0.005	0.096***
55–74	-0.080***	-0.025	-0.082***	-0.099**	-0.096***	-0.021	-0.023	0.094*
School level: some years of primary, 0–6 (reference)								
Secondary school level = 7–9	0.020***	0.053***	0.025***	0.040***	0.025**	0.080***	0.008	0.068**
High school level = 10-13	0.079***	0.171***	0.069***	0.148***	0.099***	0.199***	0.109***	0.233***
Professional level = 14–17	0.185***	0.316***	0.159***	0.300***	0.207***	0.355***	0.235***	0.346***
Postgraduate studies >16	0.308***	0.424***	0.253***	0.432***	0.334***	0.453***	0.348***	0.432***
Location size in population: less than 2,500 (reference)								
2,500–14,999	0.015**	0.052***	0.023***	0.060***	-0.012	0.037**	-0.020	0.023
15,000–99,999	0.067***	0.075***	0.082***	0.104***	0.044***	0.050***	0.015	0.038
100,000 +	0.087***	0.090***	0.106***	0.122***	0.061***	0.078***	0.045**	0.044
Average household members: 1–2 (reference)								
3–4	-0.045***	-0.036***	-0.022***	-0.026***	-0.056***	-0.033***	-0.052***	-0.039***
5–6	-0.065***	-0.061***	-0.032***	-0.037***	-0.080***	-0.056***	-0.075***	-0.085***
7+	-0.087***	-0.065***	-0.038***	-0.051***	-0.113***	-0.051***	-0.126***	-0.087***
Observations	76,098	38,027	30,440	15,211	30,448	15,214	15,210	7,602

Variables/Year	Total		Poorest (40%)		Middle (40%)		Richest (20%)	
	2018	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
Correctly classified	73.08%	73.13%	79.50%	75.01%	69.01%	70.45%	68.29%	73.52%
LR Chi2(23)	17,947.82	11,658.78	3,833.73	2,894.66	5,722.34	3,800.42	2,846.86	1,462.78
Prob >Chi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo R2	0.1816	0.2224	0.1216	0.1576	0.1396	0.1803	0.1357	0.1525

Source: prepared by the authors.
Notes: Statistical significance: * p <0.1. ** p <0.05 and *** p <0.01. Marginal effects are evaluated at the mean of each variable X. The sample was restricted to the population between 15 and 74 years of age. Household ICT assets variable estimated through Principal Component Analysis. No sample expansion factor was used.

Table A4. Scenario 1: comparison of scoring factors and summary statistics for 11 selected variables entering in the computation of the principal component analysis, 2018 and 2022

Variables/Year/ Group	Total		Poorest 40%		Middle 40%		Richest 20%	
	2018	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
Sex: man (reference)	-0.057***	-0.028***	-0.038***	-0.006	-0.061***	-0.039***	-0.092***	-0.045***
Squared age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Households ICT asset wealth: quantile 1 (reference)								
Quantile 2	0.069***	0.102***						
Quantile 3	0.125***	0.141***						
Quantile 4	0.193***	0.214***						
Quantile 5	0.269***	0.296***						
Time as Internet user: less than one year/don't remember (reference)								
Between 1 and up to 2 years	0.012	0.007	0.017	0.027	0.001	-0.033	-0.017	0.013
More than 2 and up to 5 years	0.066***	0.053	0.067***	0.063	0.060***	0.038	0.034	0.053
More than 5 years	0.202***	0.168***	0.178***	0.172***	0.219***	0.179***	0.221***	0.128***
Age group: 15–24 years old (reference)								
25–34	0.041***	0.059***	0.008	0.006	0.058***	0.085***	0.105***	0.132***
35–44	-0.008	0.025**	-0.031	-0.022	-0.008	0.036**	0.061***	0.120***
45–54	-0.046***	0	-0.058***	-0.048	-0.051*	0	0.019	0.109***
55–74	-0.083***	-0.034	-0.094***	-0.094**	-0.097***	-0.029	0.009	0.108*
School level: some years of primary = 0–6 (reference)								
Until some year of secondary school = 7–9	0.020***	0.053***	0.027***	0.040***	0.013(0	0.077***	0.04	0.075**
Until some year of high school = 10.13	0.080***	0.166***	0.070***	0.145***	0.094***	0.195***	0.127***	0.253***
Until some professional = 14–17	0.184***	0.303***	0.164***	0.288***	0.195***	0.336***	0.260***	0.371***
Postgraduate studies >17	0.304***	0.406***	0.244***	0.471***	0.329***	0.425***	0.365***	0.440***
Location size in population: less than 2,500 (reference)								
2,500–14,999	0.018**	0.054***	0.026***	0.064***	0.004	0.051**	-0.033	0
15,000–99,999	0.070***	0.076***	0.081***	0.106***	0.056***	0.068***	0.011(0.0	0.012
100,000 +	0.088***	0.091***	0.106***	0.129***	0.072***	0.100***	0.043**	0.004
Average household members: 1–2 (reference)								
3–4	-0.047***	-0.041***	-0.024***	-0.030***	-0.058***	-0.034***	-0.058***	-0,057***
5–6	-0,067***	-0,065***	-0,034***	-0,032***	-0,077***	-0,068***	-0,094***	-0,089***
7 +	-0,086***	-0,065***	-0,041***	-0,043***	-0,106***	-0,066***	-0,145***	-0,097***
Observations	76.098	38.027	31.876	15.211	30.318	15.214	13.904	7.602
LR Chi2(23)	18.102	11.659	4.047	2.895	5.391	3.800	2.432	1.463
Prob >Chi	0	0	0	0	0	0	0	0
Pseudo R2	0.1831	0.2224	0.1228	0.1576	0.132	0.1803	0.128	0.1525

Source: prepared by the authors.
Notes: statistical significance: * p<0.1. ** p<0.05 and *** p<0.01. Marginal effects are evaluated at the mean of each variable X. The sample was restricted to the population between 15 and 74 years of age. Household ICT assets variable estimated through Principal Component Analysis. A sample expansion factor was not used.

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Table A5. Scenario 2: probit regression using 11 variables for the household ICT wealth index in parsimonious models, 2018

Variables	Total	Poorest40%	Middle 40%	Richest 20%
Squared age	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Sex	-0.068*** (0.003)	-0.050*** (0.004)	-0.072*** (0.005)	-0.099*** (0.008)
Urban–rural	0.107*** (0.005)	0.122*** (0.006)	0.098*** (0.011)	0.055** (0.023)
Households ICT asset wealth: quantile 1 (reference)				
Quantile 2	0.077*** (0.005)			
Quantile 3	0.138*** (0.005)			
Quantile 4	0.215*** (0.005)			
Quantile 5	0.299*** (0.006)			
Age group (reference: 15–24 years old)				
25–34	0.047*** (0.005)	0.010(0.008)	0.066*** (0.009)	0.113*** (0.014)
35–44	-0.000128	-0.041*** (0.014)	-0.016(0.014)	0.053*** (0.020)
45–54	-0.059*** (0.013)	-0.073*** (0.021)	-0.063*** (0.021)	0.007(0.030)
55–74	-0.098*** (0.019)	-0.114*** (0.028)	-0.108*** (0.032)	-0.004(0.048)
School level (reference: until some year of primary. Maximum 6)				
Until some year of secondary school: 7–9)	0.041*** (0.006)	0.042*** (0.006)	0.037*** (0.011)	0.069*** (0.025)
Until some year of high school (10-13)	0.143*** (0.006)	0.122*** (0.006)	0.165*** (0.011)	0.204*** (0.024)
Until some high school (14–17)	0.290*** (0.006)	0.267*** (0.009)	0.313*** (0.011)	0.369*** (0.023)
Postgraduate studies (>17)	0.433*** (0.011)	0.382*** (0.033)	0.468*** (0.016)	0.489*** (0.025)
Observations	76.098	31.876	30.318	13.904
LR Chi2(23)	15.804	3.014	4.355	2.031
Prob > Chi	0	0	0	0
Pseudo R2	0.1599	0.0915	0.1066	0.1069

Source: prepared by the authors.
Notes: statistical significance: * p<0.1. ** p<0.05 and *** p<0.01. Marginal effects are evaluated at the mean of each variable X. The sample was restricted to the population between 15 and 74 years of age. Household ICT assets variable estimated through Principal Component Analysis. Standard error in parenthesis. A sample expansion factor was not used.

Table A6. Scenario 2: probit regression using 11 variables for the household ICT wealth index in parsimonious models, 2022

Variables	Total	Poorest 40%	Middle 40%	Richest 20%
Squared age	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Sex	-0.039*** (0.004)	-0.020*** (0.007)	-0.050*** (0.007)	-0.047*** (0.010)
Urban-rural	0.113*** (0.006)	0.140*** (0.007)	0.127*** (0.012)	0.026(0.023)
Households ICT asset wealth: quantile 1 (reference)				
Quantile 2	0.108*** (0.007)			
Quantile 3	0.154*** (0.007)			
Quantile 4	0.234*** (0.008)			
Quantile 5	0.319*** (0.008)			
Age group (Reference: 15–24 years old)				
25–34	0.076*** (0.007)	0.023** (0.011)	0.105*** (0.012)	0.142*** (0.019)
35–44	0.031*** (0.011)	-0.017(0.019)	0.044*** (0.017)	0.123*** (0.025)
45–54	-0.001(0.016)	-0.044(0.029)	0.001(0.025)	0.107*** (0.037)
55–74	-0.032(0.026)	-0.099** (0.043)	-0.020(0.039)	0.106* (0.057)
School level (reference: Until some year of primary. Maximum 6)				
Until some year of secondary school: 7–9)	0.070*** (0.008)	0.056*** (0.009)	0.095*** (0.014)	0.093** (0.038)
Until some year of high school (10–13)	0.216*** (0.008)	0.193*** (0.010)	0.253*** (0.014)	0.293*** (0.036)
Until some high school (14–17)	0.380*** (0.009)	0.377*** (0.014)	0.424*** (0.014)	0.425*** (0.035)
Postgraduate studies (>17)	0.490*** (0.015)	0.572*** (0.051)	0.523*** (0.021)	0.497*** (0.036)
Observations	**38.027**	**15.351**	**16.240**	**6.436**
LR Chi2(23)	**11.022**	**2.417**	**3.437**	**1.044**
Prob >Chi	**0**	**0**	**0**	**0**
Pseudo R2	**0.2102**	**0.1311**	**0.1527**	**0.1373**

Source: prepared by the authors.
Notes: statistical significance: * p<0.1. ** p<0.05 and *** p<0.01. Marginal effects are evaluated at the mean of each variable X. The sample was restricted to the population between 15 and 74 years of age. Household ICT assets variable estimated through Principal Component Analysis. Standard error in parenthesis. A sample expansion factor was not used.

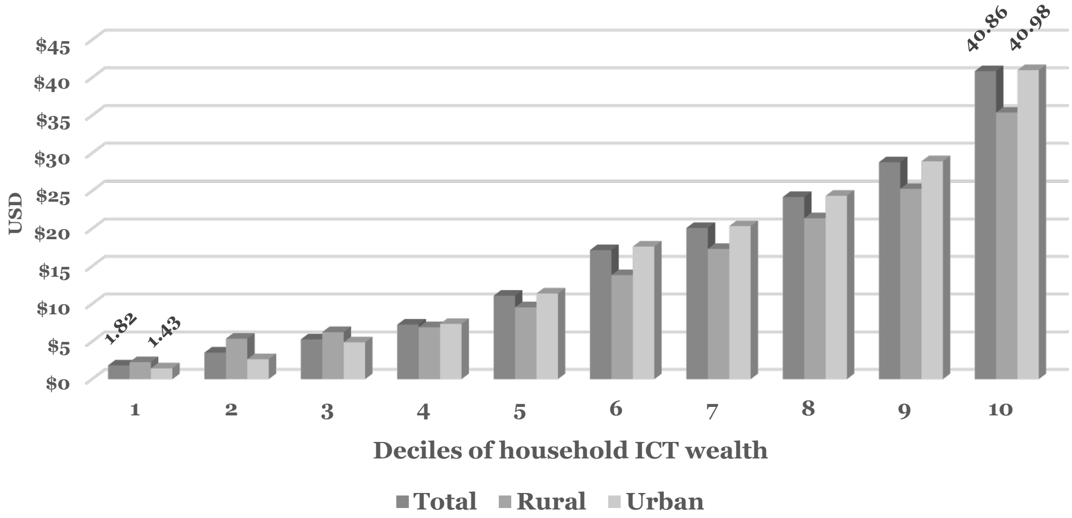

Figure A1: Average monthly spending on telecommunications services in households, grouped by ICT asset wealth, 2022 (Source: prepared by the authors)

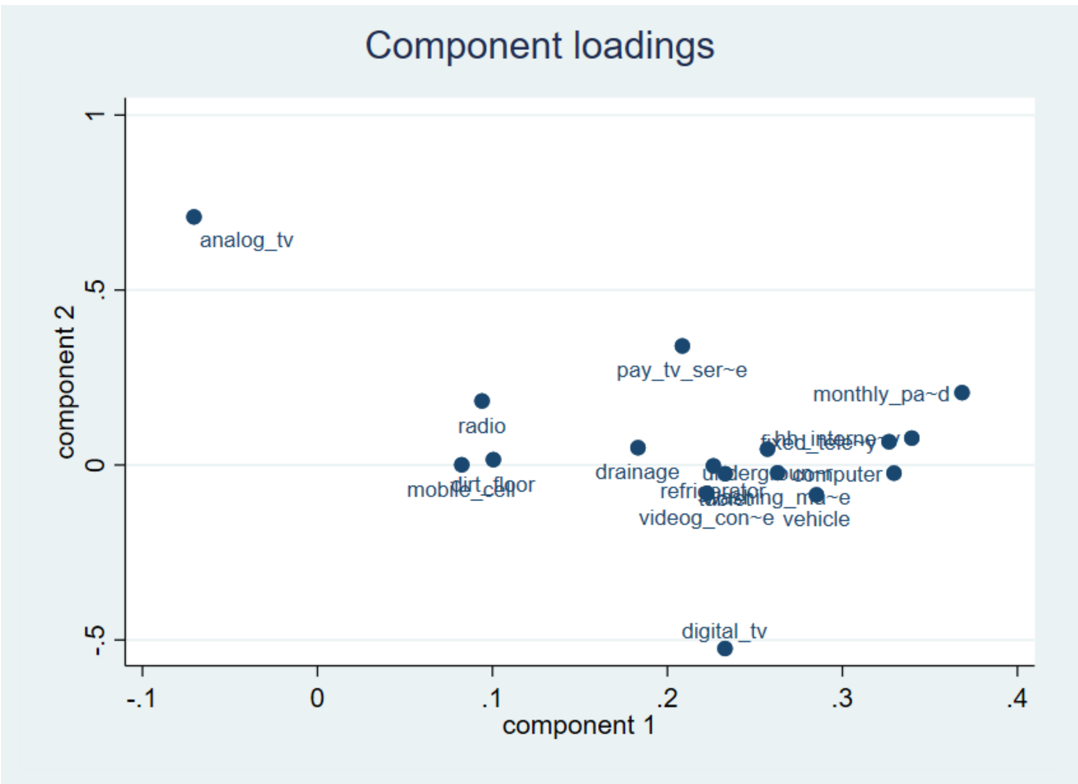

Figure A2. 2018: Loading of components 1 and 2 of the variables included in the probit models (Source: prepared by the authors)

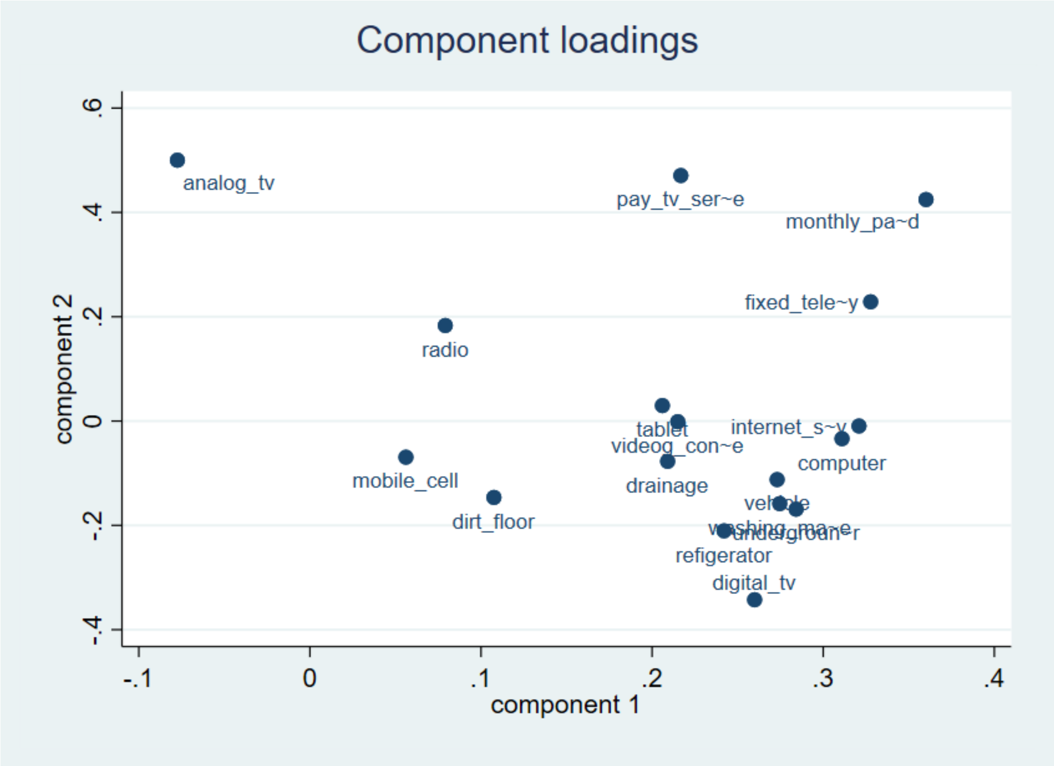

Figure A3. 2022: Loading of components 1 and 2 of the variables included in the probit models (Source: prepared by the authors)

How Important is Mobile Broadband Latency for Total Factor Productivity Growth?

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Abstract: This paper investigates the relationship between the log change in mobile broadband latency and total factor productivity (TFP) growth based on data for 130 countries. It finds that there is a strong negative correlation between TFP growth and one year lag of latency growth in OECD countries. The interpretation of the findings is that a 10 percentage points decrease in the growth of latency in period t-1 is associated with an increase of 0.3 percentage points in TFP growth. The findings are in accordance with the framework of General Purpose Technologies that suggests that the impact of new technologies often appear with a lag. Moreover, no relationship is found for the total sample or for non-OECD countries. One possible explanation could be that OECD countries have reached a higher maturity in digitalisation and automation in production processes and thus are able to take advantage of the benefits of lower latency.

Keywords: ICT, Productivity, Latency, Mobile broadband networks, Economic development

Introduction

During the last decade there has been a substantial decline in productivity growth in many OECD countries. Figure 1 shows labour productivity growth for the largest economies in the world 1995–2021. The average labour productivity growth in the OECD countries decreased from 1.4 percent in 1995–2010 to 0.9 percent in 2010–2021. The average labour productivity growth in the world increased from 2.1 percent to 2.2 percent for the same periods, respectively. Similar results have been found for total factor productivity (TFP), which is a measure that in addition to labour also includes the contributions of physical, human and other intangible capital (De Vries, 2023). Thus, productivity growth has been considerably lower in OECD countries, compared to the rest of the world.

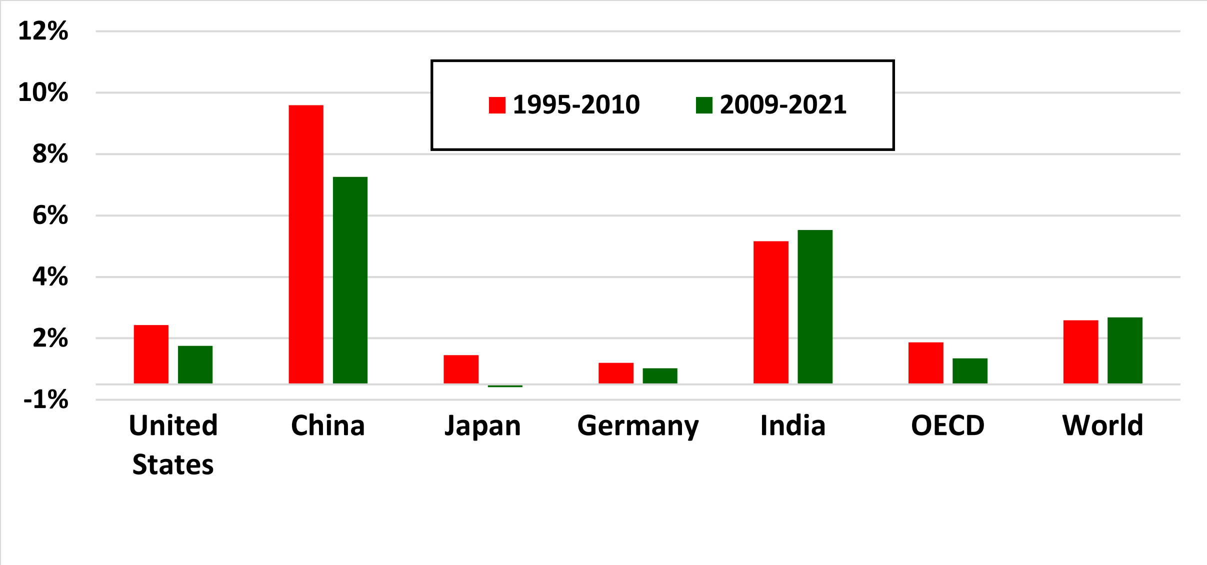

Figure 1. Annual labour productivity growth measured as GDP per person employed (constant 2017 PPP $) in the five largest economies of the world 1995–2021 (Source: World Bank, 2023a)

Over the last decade there has been large investment in new digital infrastructure e.g. 5G (5th generation mobile network) that was launched in several OECD countries in 2019. Moreover, there was also substantial investment in fixed broadband during the pandemic (ITU, 2021). The investment has improved the capabilities in the networks tremendously in terms of speed, latency, spectrum efficiency and reliability. This has implied improved high-speed connectivity that has made it possible to connect billions of devices to the cellular networks.

Despite the improved network capabilities, the productivity growth in many OECD countries has been poor. Some economists have even argued that the Solow paradox (i.e., productivity slowdown, despite progress in information and communication technology) is back at the same time as a second wave of digitalisation sweeps the world (Acemoglu *et al.*, 2014). This paper sets out to investigate the link between investment in network capabilities and productivity growth. The paper will focus on the impact of lower latency in the cellular networks and its association with productivity growth.

Latency is the time it takes for a small data packet to travel across a network from a sender to a receiver. Several studies have investigated the impact from broadband speed on economic development (see Rohman & Bohlin, 2012; Kongaut & Bohlin, 2014; Edquist, 2022). However, there is, to my knowledge, no study that has investigated how latency affects productivity development. Therefore, this paper will contribute to the literature by investigating the effect from ICT (information and communication technology) on productivity development. The methodology will start from the theory of production functions, in order to specify a model investigating the correlation between latency and TFP. The empirical analysis will be based on econometric methodology utilizing panel data for 130 countries.

The findings show a strong correlation between TFP growth and one year lag of latency growth, once controlling for labour and capital services, in OECD countries. Thus, a 10 percentage points decrease in the growth of latency in period t-1 is associated with an increase of 0.3 percentage points in TFP growth. Moreover, no relationship is found for non-OECD countries. One possible explanation could be that OECD countries have reached a higher maturity in digitalisation and automation in production processes and thus are able to take advantage of the benefits of lower latency.

Previous Literature

The relationship between ICT and economic development

There is a broad literature showing that ICT has had substantial impact on economic development and productivity (Bertschek *et al.*, 2015; Vu *et al.*, 2020). The 1980s was the decade of the personal computer in every home without any discernable effect on aggregated productivity (Solow, 1987). Thus, it was first in the second half of the 1990s that there was substantial evidence of investment in ICT having considerable economic impact. Oliner & Sichel (2000) estimated that information technology accounted for about two-thirds of the step-up in US labour productivity growth between the first and the second halves of the 1990s.

Although there were sceptics about the impact from ICT (Gordon, 2000), a number of studies clearly found evidence of a substantial impact on productivity and economic growth from ICT. Stiroh (2002b) found that ICT-producing and intensive ICT-using industries accounted for all of the productivity revival in the US. Moreover, ICT remained an important source of economic growth in the US also after the 1990s (Jorgenson *et al.*, 2008). Van Ark et al. (2008) noted that many European countries initially were lagging behind because of slower TFP growth in market services, such as trade, finance and business services. However, the overall impact of ICT capital in 59 different countries pointed towards a positive effect on GDP growth in 1995–2010 (Niebel, 2018).

In the mid-1990s there was additional evidence of the economic impact of ICT at more disaggregated levels. Basu & Fernald (2007) found that, with long time lags, ICT capital growth was positively associated with the industry TFP acceleration. Additional evidence based on industry data showed a positive return of ICT capital on output growth (O'Mahony & Vecchi, 2005). Moreover, there was evidence that European industries, that were relatively ICT intensive before 1995, outperformed the other industries post-1995 in terms of both labour productivity and TFP growth (Dahl *et al.*, 2010). There were also studies that could not find robust correlations between ICT and economic development based on industry data

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(Stiroh 2005; Basu *et al*., 2003). However, the overall conclusion based on the literature points in the direction of positive correlations between ICT and economic development.

Research, analyzing the firm level, found a robust relationship between ICT and economic development. Brynjolfsson & Hitt (2003) showed that computer capital was correlated with TFP growth for US firms when the average growth rates over longer time periods were used. The results were not robust to using first differences, but the estimated coefficients increased in size when the length of the growth period increased. Additional studies found evidence of economic impact from ICT at the firm level (van Leeuwen & van der Wiel, 2003; Van Reenen *et al*., 2010; Zhang *et al*., 2022). Moreover, based on two European datasets, it was also shown that US multinationals appeared to obtain higher productivity than non-US multinationals from their ICT capital investments (Bloom *et al*., 2012). Thus, ICT may lead to changes in firms' organisational structure that differs across firms.

Investigations of the "C" in ICT

While there has been a plethora of papers investigating the economic impact of all types of ICTs, there is much less research investigating the impacts of specific varieties of ICT equipment. Goodridge et al. (2019) divided ICT capital into computer software, hardware, and communication capital. Their findings suggested that price deflators are important for estimating the contribution of each capital type.

In a seminal paper, Röller & Waverman (2001) found a significant relationship between telecommunications infrastructure and aggregate output based on 21 OECD countries in 1971–1990. Their findings suggested that one-third of economic growth could be attributed to telecommunications after controlling for simultaneity and country-specific fixed effects. Moreover, Gruber & Koutroumpis (2011), based on data for 192 countries, found that investment in telecommunications infrastructure contributed 0.2 percentage points to economic growth in high income countries in 1990–2007.

There are also a number of papers investigating the impact of fixed broadband. Czernich et al. (2011) found that a 10 percentage points increase in fixed broadband penetration raised annual per capita growth by 0.9–1.5 percentage points in 21 OECD countries in 1996–2007. Gruber et al. (2014) also found evidence that fixed broadband had a positive effect on GDP for 27 EU-countries in 2005–2011. On the contrary, Thomson & Garbacz (2011) found no strong significant impact from fixed broadband adoption on GDP per household based on 43 different countries in 2005–2009. However, the results based on mobile broadband suggested a significant impact on GDP per household. Moreover, Edquist et al. (2018) found that there was a statistically significant effect from mobile broadband on GDP in 2002–2014. The results

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were significant both when mobile broadband was first introduced and gradually as it diffused in different economies.

An additional stream of papers has investigated the economic impact from different capabilities of fixed and mobile broadband networks. These studies are primarily focused on the effect of download speed in the networks. Briglauer & Gugler (2019) found a small but significant effect of fixed fibre-based adoption on GDP compared to basic fixed broadband. Rohman & Bohlin (2012) showed that the doubling of fixed broadband speed contributed 0.3 percentage points to economic growth compared to growth rate in the base year in 34 OECD countries. Additional studies have found supporting evidence that fixed broadband speed contributed to GDP, but that the impact was greater in countries with lower incomes (Kongaut & Bohlin, 2014). Moreover, Edquist (2022) investigated the impact of download speed in the mobile broadband networks in 116 countries in 2014–2019. The results showed that a one-year lag of median download speed was significantly associated with labour productivity, but there was no evidence of a contemporaneous association.

General purpose technologies and the lagged effect

According to Bresnahan & Trajtenberg (1995), whole eras of technical progress are driven by a few General Purpose Technologies (GPTs) with the following characteristics: (1) pervasiveness, which implies that the technology diffuses extensively throughout the economy; (2) technical improvements, meaning that the technology continuously improves performance and lowers cost; (3) innovational complementarities, implying that the technology leads to improvements in R&D and innovational efforts.

The effects from GPTs on productivity are often delayed, since many GPTs require organizational restructuring to reach their full potential (Helpman, 1998). At first, the new technology may only perform the same function as the old technology, which was the case when electric motors replaced steam engines in the early 20th century (Devine, 1983). However, as more electric motors were installed in factories, it was possible to let each machine be run by an individual electric motor and thus reorganise the whole production layout of the factory in a more productive manner. According to Greenwood (1999), it was no longer necessary to shut down the entire power system for maintenance. Thus, the quantity and quality of output increased as each machine could be controlled individually and located to optimise flexibility in the production process. This process implied that existing productive capital was creatively destroyed, which further delayed the positive productivity effects at the more aggregate level.

According to the GPT literature, another reason for the delayed productivity effects from new technology is innovational complementarities. An invention by itself would have little economic effect if there was no scope for the users of the new technology to improve their own technologies (Edquist & Henrekson, 2006). For example, before electricity could be used in manufacturing, several types of electric machines had to be invented. Hence, it is rather the applications of a wireless network that result in productivity gains than the network by itself.

ICT is believed to fulfill the requirements of being a GPT (Vu *et al.*, 2020). There are a number of different studies that have pointed out that the effects on productivity from new technology often appear with a lag (David, 1990; Brynjolfsson & Hitt, 2003; Edquist & Henrekson, 2017). These empirical findings support the view of the GPT framework that it takes time from the moment of the original invention until a substantial increase in the rate of productivity growth can be observed.

Latency and its implications for productivity

Latency is the time it takes for a small data packet to travel across the network from a sender to a receiver and for the response to come back (Sundaresan *et al.*, 2020). This way of measuring latency is known as Round Trip Time (RTT). RTT is the latency perceived by the end-user (NGNM, 2015). There is also one way-latency, which is the total time it takes for a packet of data to travel from the sender to the receiver. According to Sundaresan et al. (2020), it may be complicated to measure one-way latency as it implies that the sender and receiver have synchronised clocks, which sometimes is a challenge to set up and maintain when the end points are across multiple domains.

Data on the Internet may travel with the speed of light, but the effects of distance and delays caused by the Internet infrastructure equipment imply that latency cannot be completely eliminated. Moreover, data traversing the Internet often has to cross multiple networks. The more networks the data packet needs to pass through, the larger is the probability of delay.

As the world has become more digital, the impact from latency on productivity is believed to have increased substantially. One reason is that businesses have become more reliant on cloud applications (Dar, 2018). In recent years it has become common that employees use video conferencing for sales purposes and information sharing. Moreover, cloud-based management tools are used to access information, share files and perform business processes. It is evident that high latency will slow down these processes, which most certainly also effects the productivity among employees.

In the last year the impact from Internet of Things (IoT) have become increasingly important for productivity (Edquist *et al.*, 2021). The interconnected devices that are used for personal and business tasks are dependent on the fast transfer of information. Thus, latency and reliability play a vital role in the smooth operations of IoT devices (Siddiqi *et al.*, 2019).

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Methodology

To investigate the association between latency and total factor productivity (TFP), the methodology in this paper is based on econometric methods. The econometric model in this paper follows the neoclassical production function (Solow, 1956). Assuming an augmented Cobb-Douglas production function (Cobb & Douglas, 1928), we have the following equation:

$$V_{i,t} = TFP_{i,t} K_{i,t}^{S_K} L_{i,t}^{S_L} \tag{1}$$

where $V_{i,t}$ is real value added, $K_{i,t}$ is capital, $L_{i,t}$ is labour input, S_K is the output elasticity of capital, S_L is the output elasticity of labour and $TFP_{i,t}$ is Hicks-neutral TFP, all for country *i* at time *t*.

Taking natural logarithms of and first differencing equation (1) gives:

$$\Delta \ln V_{i,t} = s_K \Delta \ln K_{i,t} + s_L \Delta \ln L_{i,t} + \Delta \ln TFP_{i,t} \tag{2}$$

Based on the growth accounting framework it is assumed that markets are competitive and there are constant returns to scale, which implies that the elasticities S_K and S_L are equal to each factor's income share (Solow, 1957). Thus, by transforming equation (2), TFP can be estimated as follows:

$$\Delta \ln TFP_{i,t} = \Delta \ln V_{i,t} - s_K \Delta \ln K_{i,t} - s_L \Delta \ln L_{i,t} \tag{3}$$

Equation (3) shows that ΔTFP is measured as a residual, which implies that there might be measurement errors in capital and labour inputs. Moreover, there might also be unmeasured intangible capital (Corrado *et al.*, 2009; Marrano *et al.*, 2009). However, TFP could also be caused by organizing production processes in a smarter (more productive) way (Stiroh, 2002a).

Lower latency improves the quality of a network and primarily affects cloud and IoT applications, which in the longer run leads to reorganization and rationalization. Thus, it is likely that latency would be affecting TFP growth. These productivity enhancing applications can first be fully acknowledged once the latency has been reduced to a certain level. Moreover, the GPT literature suggests that the productivity effects would take time due to reorganizations of production. It would therefore be of interest to estimate an equation that tests whether latency is correlated with TFP growth. The econometric specification is based on first differences in order to control for country fixed effects.

$$\Delta \ln TFP_{i,t} = \beta_1 + \beta_2 \Delta \ln Latency_{i,t} + \beta_3 \Delta \ln K_{i,t} + \beta_4 \Delta \ln LS_{i,t} + \beta_5 \Delta \ln X_{i,t} + \delta_t + v_{i,t} \tag{4}$$

where $\Delta lnTFP_{i,t}$ is the change in log TFP in country *i*, $\Delta lnLatency_{i,t}$ is the change in log latency, $\Delta lnK_{i,t}$ is the change in log capital services, $\Delta lnLS_{i,t}$ is the change in log labour services, $\Delta lnX_{i,t}$

is the change in any additional control variables, δ_t are year dummies which capture common economic shocks, and $v_{i,t}$ is the differenced residual.

As shown above, TFP is measured as a residual in a growth accounting framework. This implies that TFP is only measured in terms of first differences and not in level estimates. Moreover, the concept of the level of capital services is also unclear (Inklaar & Timmer, 2008). Therefore, the specification will be based on first differences. By using first differences it is still possible to control for country fixed effects. However, it will not be possible to conduct panel data analysis based on levels.

Data

The purpose of this paper is primarily to investigate the association between TFP and latency in the cellular network. The dependent variable TFP growth is based on the Total Economy Database (Conference Board, 2022). It is measured as a residual and accounts for the changes in output not caused directly by change in capital and labour services. Thus, it represents the effect of technological change, efficiency improvements, innovation and inability to measure the contribution of all other inputs (De Vries & Erumban, 2022).

The main independent variable of interest is latency. Latency data is based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021 (Ookla, 2022). The database presents data from millions of tests and readings collected via Speedtest, which is an app service used to test the speed and latency of a particular mobile device. Latency is measured as round-trip time (RTT) in milliseconds. One potential bias with collecting the latency data is that people might be more eager to run the speed test when they are close to a base station. Moreover, it is also likely that many users run the speed test when the network is not working appropriately. To minimise these measurement errors, the median latency is used instead of the average latency. Moreover, as long as these biases are similar among countries, the measurement error will be similar in all countries.

According to the production function theory, the growth of capital and labour services should be included as additional independent variables. The data of the growth of capital and labour services and TFP are based on the Total Economy Database (Conference Board, 2022). Capital services growth refers to the change in the flow of productive services provided by capital assets, such as buildings, transport equipment and machines. The underlying capital stock is based on six different asset types that are calculated from national accounts' investment data using the perpetual inventory method. The aggregation of the growth in capital over the different types is based on a user cost approach (De Vries & Erumban, 2022). Labour services have been constructed by aggregating the change in labour quantity and quality. Labour quantity is based on total hours worked or total persons engaged, while labour quality is based

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on a measure in the changes of the composition of the workforce, which is based on data on employment and wages by educational attainment.

In the robustness section, we introduce mobile download speed as an additional independent variable. Download speed data is based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021 (Ookla, 2022). Download speed is measured in kilobits per second (kbps). There are a number of research articles that have found associations between economic development and speed in fixed and cellular networks (i.e., Briglauer & Gugler, 2019; Rohman & Bohlin, 2012; Kongaut & Bohlin, 2014; Edquist, 2022). In addition to speed, the change in the size of manufacturing in each country (measured as the share of GDP in percent) is also included as a control variable. The manufacturing share is based on the World Bank (2023a). The change in the size of manufacturing may have an impact on TFP as Internet of Things and machine learning are believed to have a larger impact in manufacturing.

Table 1. Countries included in the regressions divided into OECD and non-OECD countries

OECD countries (38)	Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States
Non-OECD countries (92)	Albania, Algeria*, Angola*, Argentina, Armenia, Azerbaijan, Bahrain, Bangladesh*, Belarus, Bolivia*, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso*, Cambodia*, Cameroon*, Chad*, China, Congo*, Croatia, Cyprus, Côte d'Ivoire*, DR Congo*, Dominican Republic, Ecuador, Egypt*, Ethiopia*, Gabon, Georgia, Ghana*, Guatemala, Hong Kong, India*, Indonesia*, Iran*, Iraq, Jamaica, Jordan, Kazakhstan, Kenya*, Kuwait, Kyrgyzstan*, Lebanon*, Libya, Madagascar*, Malawi*, Malaysia, Mali*, Malta, Mauritius, Moldova, Morocco*, Mozambique*, Myanmar*, Namibia, Niger*, Nigeria*, North Macedonia, Oman, Pakistan*, Paraguay, Peru, Philippines*, Qatar, Romania, Russia, Rwanda*, Saudi Arabia, Senegal*, Serbia, Singapore, South Africa, Sri Lanka*, Sudan*, Syria*, Taiwan, Tanzania*, Thailand, Trinidad and Tobago, Tunisia*, Turkmenistan, Uganda*, Ukraine*, United Arab Emirates, Uruguay, Uzbekistan*, Venezuela, Vietnam*, Yemen*, Zambia*, Zimbabwe*

Note: *indicates that the country is defined as a low-income country i.e. has GNI per capita below $4256.

In total, data for 130 countries are used in the regression analysis for the period 2014–2021. The analysis is based on a balanced panel for all variables included in the respective regressions. Thus, all countries with missing data for a specific variable that is included in the specific regression analysis have been dropped. Table 1 shows a list of the countries that have been included in the regressions, divided into OECD and non-OECD countries. Moreover, Table 2 shows some descriptive statistics.

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Table 2. Descriptive statistics (2014–2021)

Variables	Mean	St. Dev.	Min	Max	No. obs
All countries					
Log change in total factor productivity (ΔlnTFP)	−0.008	0.05	−0.85	0.50	910
Log change in median latency (ΔlnLatency)	−0.19	0.26	−1.76	1.05	910
Log change in labour services (ΔlnLS)	0.006	0.01	−0.05	0.17	910
Log change in capital services (ΔlnK)	0.04	0.03	−0.08	0.19	910
Log change in download speed (ΔlnSpeed)	0.30	0.34	−0.83	2.93	910
Change in the share of manufacturing (in % of GDP) (ΔMfg)	0.05	1.03	−7.76	15.11	798
OECD countries					
Log change in total factor productivity (ΔlnTFP)	0.0006	0.02	−0.14	0.07	266
Log change in median latency (ΔlnLatency)	−0.13	0.13	−0.78	0.09	266
Log change in labour services (ΔlnLS)	0.005	0.007	−0.04	0.04	266
Log change in capital services (ΔlnK)	0.03	0.02	−0.01	0.19	266
Log change in download speed (ΔlnSpeed)	0.25	0.20	−0.37	1.07	266
Change in the share of manufacturing (in % of GDP) (ΔMfg)	0.04	1.11	−1.66	15.11	252
Non-OECD countries					
Log change in total factor productivity (ΔlnTFP)	−0.01	0.06	−0.85	0.50	644
Log change in median latency (ΔlnLatency)	−0.22	0.29	−1.76	1.05	644
Log change in labour services (ΔlnLS)	0.006	0.01	−0.05	0.17	644
Log change in capital services (ΔlnK)	0.04	0.04	−0.08	0.18	644
Log change in download speed (ΔlnSpeed)	0.32	0.38	−0.83	2.93	644
Change in the share of manufacturing (in % of GDP) (ΔMfg)	0.06	0.99	−7.76	7.84	546

Note: Latency and download speed data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

Results

Main results

Table 3 presents the aggregate result based on the total sample of 130 countries. It shows that there is no significant relationship between TFP growth and the change in log of mobile broadband latency. Moreover, when three years differences are included, there is still no evidence of any significant relationship.

Table 4 includes the change in log of latency that has been lagged by one year. However, there is still no significant correlation between the lagged latency variable and TFP growth. Moreover, when we include both the change in the log of latency and its lag, there is no significant correlation with TFP growth. Thus, there is little evidence of any association between TFP growth and the change in the log of latency for our total sample of 130 countries.

Table 3. Regressions of the relationship between TFP growth and the change in the log of latency

	Dependent variable: TFP growth (ΔlnTFP)	
	First differences	**Three years differences**
ΔLog of latency (ΔlnLatency)	−0.002 (0.008)	−0.02 (0.020)
ΔLog of labour services (ΔlnLS)	−0.33*** (0.099)	−0.23 (0.308)
ΔLog of capital services (ΔlnK)	0.01 (0.141)	0.04 (0.176)
Constant	−0.007 (0.009)	−0.03 (0.032)
Year dummies	Yes	Yes
R^2	0.06	0.04
Number of observations	910	650

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Latency data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

Table 4. Regressions of the relationship between TFP growth and the change in the log and lagged log of latency

	Dependent variable: TFP growth (ΔlnTFP)		
	First differences	**Lagged differences**	**First + lagged differences**
ΔLog of latency (ΔlnLatency)	−0.002 (0.008)		−0.009 (0.011)
ΔLog of latency (ΔlnLatency) (t−1)		−0.005 (0.006)	−0.005 (0.006)
ΔLog of labour services (ΔlnLS)	−0.33*** (0.099)	−0.28** (0.119)	−0.29** (0.118)
ΔLog of capital services (ΔlnK)	0.01 (0.141)	−0.003 (0.159)	−0.005 (0.160)
Constant	−0.007 (0.009)	−0.009 (0.010)	−0.01 (0.010)
Year dummies	Yes	Yes	Yes
R^2	0.06	0.06	0.07
Number of observations	910	780	780

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Latency data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

To further investigate the impact from latency, the sample is divided into OECD and non-OECD countries. Table 5 shows that there is still no significant relationship between the change in log of mobile broadband latency and TFP growth in OECD and non-OECD countries, respectively. The same holds for three years differences.

Table 5. Regressions of the relationship between TFP growth and the change in the log of latency for OECD and non-OECD countries

	Dependent variable: TFP growth (ΔlnTFP)			
	First differences		**Three years differences**	
	OECD	**Non-OECD**	**OECD**	**Non-OECD**
ΔLog of latency (ΔlnLatency)	0.004 (0.012)	−0.007 (0.009)	−0.012 (0.021)	−0.03 (0.023)
ΔLog of labour services (ΔlnLS)	−0.14 (0.230)	−0.32*** (0.119)	−0.03 (0.373)	−0.10 (0.395)
ΔLog of capital services (ΔlnK)	−0.29 (0.233)	0.08 (0.158)	−0.25 (0.239)	0.11 (0.200)
Constant	0.01* (0.008)	−0.018 (0.012)	0.03 (0.021)	−0.07 (0.049)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.31	0.05	0.20	0.05
Number of observations	266	644	190	460

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Latency data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

Table 6. Regressions of the relationship between TFP growth and the change in the log and lagged log of latency

	Dependent variable: TFP growth (ΔlnTFP)					
	First differences		**Lagged differences**		**First + lagged differences**	
	OECD	**Non-OECD**	**OECD**	**Non-OECD**	**OECD**	**Non-OECD**
ΔLog of latency (ΔlnLatency)	0.004 (0.012)	−0.007 (0.009)			0.02 (0.016)	−0.01 (0.011)
ΔLog of latency (ΔlnLatency) (t−1)			−0.03*** (0.010)	−0.009 (0.008)	−0.03*** (0.010)	−0.01 (0.008)
ΔLog of labour services (ΔlnLS)	−0.14 (0.230)	−0.32*** (0.119)	−0.14 (0.274)	−0.28** (0.134)	−0.12 (0.281)	−0.28** (0.134)
ΔLog of capital services (ΔlnK)	−0.29 (0.233)	0.08 (0.158)	−0.31 (0.250)	0.07 (0.181)	−0.31 (0.251)	0.07 (0.181)
Constant	0.014* (0.008)	−0.018 (0.012)	0.0006 (0.006)	−0.02 (0.014)	0.005 (0.008)	−0.025 (0.015)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.31	0.05	0.33	0.06	0.33	0.06
Number of observations	266	644	228	552	228	552

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Latency data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

In Table 6, the lagged change in the log of latency is introduced for OECD and non-OECD countries. The lagged change in the log of latency is still insignificant for non-OECD countries, but highly significant for OECD countries at the one percent level. The results suggest that a 10 percentage points decrease in the growth of latency in period *t*-1 is associated with a 0.3 percentage points increase in TFP growth in OECD countries. When both the change in the log of latency and its lag are introduced in the regression analysis, the results for the lagged variable remain highly significant for OECD countries. Moreover, based on an F-test, it is possible to reject the hypothesis that both the first differences and the lagged differences are jointly equal to zero at the 1 percent level.

Robustness

Latency is not the only capability of a mobile broadband network that may be important for productivity in the economy. There is, for example, evidence that the speed in fixed broadband is important for economic development (Kongaut & Bohlin, 2014; Briglauer & Gugler, 2019). Moreover, there is also evidence of a lagged effect from mobile broadband speed on labour productivity (Edquist, 2022). In order to test the robustness of the results, the change in log of speed is introduced as an independent control variable. In addition, machine learning and IoT may primarily impact automation in manufacturing. Therefore, a control variable, measuring the size of manufacturing (in percent of GDP), is also introduced.

Table 7. Regressions of the relationship between TFP growth and the change in the log and lagged log of latency

	Dependent variable: TFP growth (ΔlnTFP)					
	First differences		**Lagged differences**		**First + lagged differences**	
	OECD	**Non-OECD**	**OECD**	**Non-OECD**	**OECD**	**Non-OECD**
ΔLog of latency (ΔlnLatency)	−0.0001 (0.014)	0.006 (0.006)			0.01 (0.019)	−0.0008 (0.007)
ΔLog of latency (ΔlnLatency) (t−1)			−0.03*** (0.012)	−0.003 (0.005)	−0.03*** (0.012)	−0.003 (0.005)
ΔLog of labour services (ΔlnLS)	−0.14 (0.229)	−0.44*** (0.074)	−0.11 (0.259)	−0.42*** (0.066)	−0.10 (0.268)	−0.42*** (0.066)
ΔLog of capital services (ΔlnK)	−0.29 (0.235)	−0.14** (0.066)	−0.32 (0.263)	−0.14** (0.069)	−0.32 (0.263)	−0.14** (0.069)
ΔLog of download speed (ΔlnSpeed)	−0.005 (0.006)	−0.007 (0.007)	−0.006 (0.007)	−0.008 (0.010)	−0.004 (0.009)	−0.008 (0.010)
ΔManufacturing size in (% of GDP) (ΔMfg)	0.0003 (0.0005)	0.001 (0.003)	−0.001 (0.003)	0.001 (0.003)	−0.001 (0.003)	0.001 (0.003)
Constant	0.02* (0.008)	−0.01* (0.007)	0.001 (0.006)	0.006 (0.008)	0.004 (0.008)	0.006 (0.008)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.33	0.14	0.35	0.14	0.35	0.14
Number of observations	252	546	216	468	216	468

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Latency and download speed data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021.

Table 7 shows that the lagged latency variable remains robust for OECD countries once the change in the log of speed and the change in the size of manufacturing are included as control variables. When we include both the change in log of latency and its lag, the lagged variable remains highly significant. Based on an F-test, it is possible to reject the hypothesis that both variables are jointly equal to zero at the 5% significance level.

So far countries have been divided into OECD and non-OECD countries, where OECD countries are based on the members of the OECD, i.e., some of the most industrialised countries in the world. However, countries could also be grouped based on income level. Thus, to further test the robustness of our findings, the sample is split into four different country groups. The World Bank (2023b) provides a classification of different countries based on income. The country groups are as follows in terms of GNI per capita in 2022: low income, $1,085 or less; lower middle income, $1,086 to $4,255; upper middle income, $4,256 to $13,205; and high income, $13,206 or more. Table 8 shows that there is no significant relationship between the lagged log change of latency and TFP growth for any of the country groups. Thus, it appears that the significant relationship only holds for OECD countries.

Simultaneity

One general problem with studies investigating the impact from ICT on productivity is simultaneity. Simultaneity implies that latency can be both a driver and a result from increased TFP growth. It is not unlikely that countries that achieve higher TFP growth also are able to invest more in mobile broadband networks and thus reduce latency. One approach to deal with simultaneity is to use instrumental variables that are correlated with the explanatory variables but not with the error term (Czernich *et al.*, 2011). However, it has not been possible to find valid instruments for mobile broadband latency.

Another approach is to use lagged variables as instruments. However, this method has been criticised by Reed (2015), who finds that it is not possible to escape simultaneity bias. A third method would be to use lagged values in 2SLS and GMM estimations. According to Reed (2015), this would only work if the lagged variables used do not themselves belong to the respective estimation equation and if they are sufficiently correlated with the simultaneously determined explanatory variable, i.e., latency. Based on earlier findings on the impact of ICT (Basu & Fernald, 2007; Brynjolfsson & Hitt, 2003), the lagged variable of latency belongs to the estimation equation. Thus, the method to correct for simultaneity is not attempted.

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Table 8. Regressions of the relationship between TFP growth and the change in the log and lagged log of latency

First differences

	Dependent variable: TFP growth (ΔlnTFP)			
	First differences			
	Low-Income	**Lower Middle-Income**	**Upper Middle-Income**	**High-Income**
ΔLog of latency (ΔlnLatency)	0.004 (0.006)	0.001 (0.010)	0.02* (0.011)	0.01 (0.015)
ΔLog of latency (ΔlnLatency) (t-1)				
ΔLog of labour services (ΔlnLS)	0.33 (0.382)	−0.51 (0.375)	−0.39*** (0.132)	−0.33*** (0.067)
ΔLog of capital services (ΔlnK)	−0.21 (0.127)	0.03 (0.114)	−0.21 (0.198)	−0.52*** (0.109)
ΔLog of download speed (ΔlnSpeed)	0.002 (0.008)	0.002 (0.003)	−0.03 (0.012)	−0.01* (0.006)
ΔManufacturing size in (% of GDP) (ΔMfg)	0.002 (0.004)	0.004 (0.004)	−0.0006 (0.003)	−0.002 (0.002)
Constant	0.02 (0.014)	0.002 (0.010)	0.03 (0.014)	0.03 (0.007)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.22	0.12	0.18	0,46
Number of observations	70	182	231	315

Lagged differences

	Dependent variable: TFP growth (ΔlnTFP)			
	Lagged differences			
	Low-Income	**Lower Middle-Income**	**Upper Middle-Income**	**High-Income**
ΔLog of latency (ΔlnLatency)				
ΔLog of latency (ΔlnLatency) (t-1)	0.001 (0.009)	0.004 (0.008)	0.004 (0.010)	−0.02 (0.018)
ΔLog of labour services (ΔlnLS)	0.30 (0.442)	−0.65 (0.464)	−0.24* (0.137)	−0.33*** (0.064)
ΔLog of capital services (ΔlnK)	−0.20 (0.143)	−0.003 (0.131)	−0.12 (0.193)	−0.58*** (0.116)
ΔLog of download speed (ΔlnSpeed)	0.001 (0.008)	0.009 (0.005)	−0.04* (0.018)	−0.02** (0.007)
ΔManufacturing size in (% of GDP) (ΔMfg)	0.001 (0.004)	0.004 (0.005)	−0.0002 (0.003)	−0.009*** (0.003)
Constant	0.004 (0.012)	−0.001 (0.012)	0.02 (0.014)	0.01 (0.008)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.20	0.13	0.17	0.50
Number of observations	60	156	198	270

First + lagged differences

	Dependent variable: TFP growth (ΔlnTFP)			
	First + lagged differences			
	Low-Income	**Lower Middle-Income**	**Upper Middle-Income**	**High-Income**
ΔLog of latency (ΔlnLatency)	−0.0008 (0.007)	−0.004 (0.008)	0.03* (0.014)	0.03 (0.023)
ΔLog of latency (ΔlnLatency) (t-1)	0.002 (0.009)	0.004 (0.008)	0.009 (0.009)	−0.02 (0.017)
ΔLog of labour services (ΔlnLS)	0.30 (0.482)	−0.65 (0.460)	−0.22 (0.141)	−0.34*** (0.065)
ΔLog of capital services (ΔlnK)	−0.20 (0.149)	−0.004 (0.131)	−0.12 (0.189)	−0.58*** (0.116)

	Dependent variable: TFP growth (ΔlnTFP)			
	First + lagged differences			
	Low-Income	Lower Middle-Income	Upper Middle-Income	High-Income
ΔLog of download speed (ΔlnSpeed)	0.0005 (0.011)	0.008 (0.006)	−0.03* (0.016)	−0.01* (0.007)
ΔManufacturing size in (% of GDP) (ΔMfg)	0.001 (0.004)	0.004 (0.005)	0.001 (0.003)	−0.009*** (0.003)
Constant	0.004 (0.012)	−0.002 (0.013)	0.03* (0.018)	0.02* (0.009)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.20	0.13	0.18	0.51
Number of observations	60	156	198	270

Note: The estimates are based on pooled Ordinary Least Squares (OLS). Cluster robust standard errors are presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Venezuela is included in the total sample, but it has been excluded when the sample is divided into different income classifications because it has not been classified by the World Bank (2023). Latency and download speed data based on analysis by Ericsson of Ookla® Speedtest Intelligence® data for 2014–2021. The country groups are as follows in terms of GNI per capita in 2022: low income, $1,085 or less; lower middle income, $1,086 to $4,255; upper middle income, $4,256 to $13,205; and high income, $13,206 or more.

Discussion of Results

There is a broad literature on the economic impact of ICT (e.g., Bertschek *et al.*, 2015; Vu *et al.*, 2020; Oliner & Sichel, 2000; Gordon, 2000; Jorgenson *et al.*, 2008; Van Ark *et al.*, 2008). The findings of this paper add knowledge to the literature by showing that there is an association between the lagged change of latency in the mobile broadband network and TFP growth in OECD countries. While the economic impact of fixed and mobile broadband and the speed in the networks have been investigated before (Rohman & Bohlin, 2012; Kongaut & Bohlin, 2014; Briglauer & Gugler, 2019; Edquist, 2022), there is a lack of knowledge about the impact of latency.

As pointed out in the literature section, the GPT literature suggests that there might be a lagged effect from new technology. The most famous example is the Nobel Laureate Robert Solow observing, in the 1980s, that the computer age could be seen everywhere but in the productivity statistics. One explanation for a delayed effect might be that applications that need lower latency also require organizational restructuring (Helpman, 1998). An additional explanation might be that innovational complementarities, such as new applications that require low latency, are necessary before productivity gains are achieved. This implies that there might be a lagged effect from latency.

The lagged specification used in this paper implies that the change of the dependent variable between two points in time is a function of the specified difference of the independent variable between the preceding points in time (Leszczensky & Wolbring, 2019). This implies that the model with a lagged change in the log of latency is only appropriate if the lags in the panel data match the real-world causal lags in the process under study (Vaisey & Miles, 2017). However, according to the literature on General Purpose Technologies, there is reason to believe that latency would have a lagged effect on productivity, as it takes time for new technology to affect productivity growth (David, 1990; Brynjolfsson & Hitt, 2003).

The findings that the lagged variable is only significant for OECD countries is also of interest. One possible explanation could be that OECD countries have reached a higher maturity in digitalisation and automation in production processes and thus are able to take advantage of the benefits of lower latency. One indicator of digital maturity that is important from a latency perspective is IoT penetration, i.e., IoT connections per 100 inhabitants. According to Edquist et al. (2021), IoT connections have increased considerably during the last decade worldwide. IoT devices that are used for personal and business tasks are dependent on fast transfer of information, which implies that latency plays a vital role in the smooth operations of these devices (Siddiqi *et al.*, 2019).

Figure 2 shows that IoT connections per 100 inhabitants in OECD and non-OECD countries are quite similar. However, if China is excluded, the difference between OECD and non-OECD countries increases considerably. In 2023, OECD countries had 45 IoT connections per 100 inhabitants, while the corresponding figure for non-OECD countries, excluding China, was only 5. This is a clear indication that OECD countries have reached a higher maturity in digitalisation compared to non-OECD countries excluding China. China is an exception with high IoT connections per 100 inhabitants, which shows the enormous digitalisation that has taken place in the Chinese economy since 2010. However, China only has a minor impact in the econometric analysis since all countries that are included have the same weight.

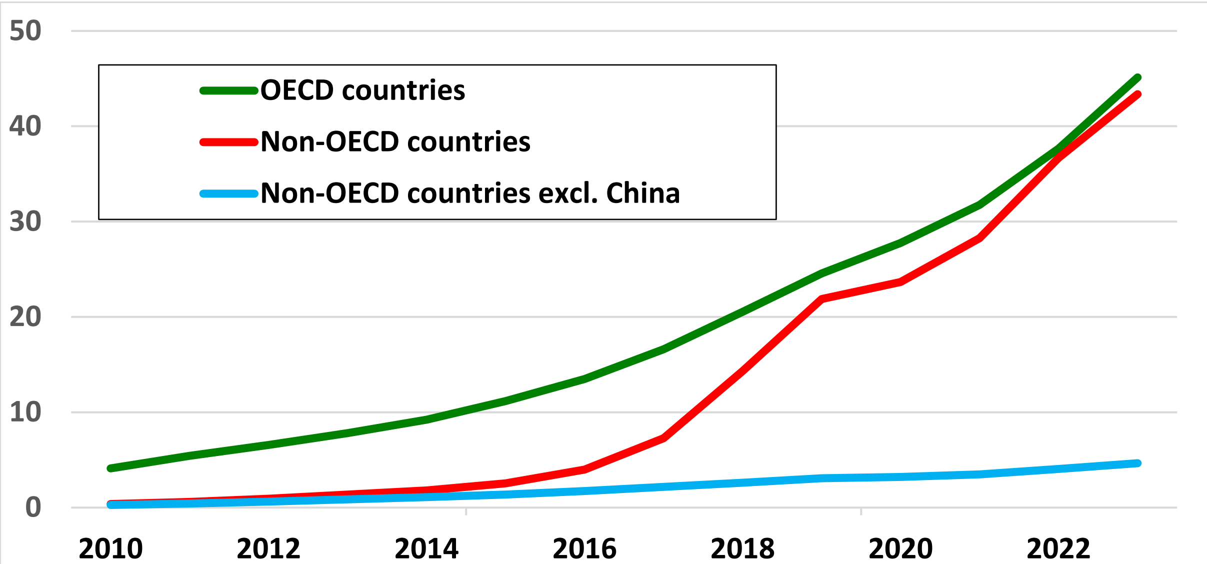

Figure 2. IoT devices per 100 inhabitants in OECD and non-OECD countries (including and excluding China) 2010–2023. (Source: GSMA, 2024). **Note: The Figure is based on data for 169 countries.**

Conclusions

This paper has investigated the relationship between the log change in mobile broadband latency and TFP growth based on data for 130 countries. It finds no correlation between the log change of mobile broadband latency and TFP growth for the total sample. However, there is a strong negative relationship (at the one percent level) between the log change in the one-year lag of latency and TFP growth in OECD countries. Thus, a 10 percentage points decrease in the growth of latency in period t-1 is associated with an increase of 0.3 percentage points in TFP growth in OECD countries.

The lagged specification implies that the change of the dependent variable between two points in time is a function of the specified difference of the independent variable between the preceding points in time (Leszczensky & Wolbring, 2019). This implies that the model with a lagged change in the log of latency is only appropriate if the lags in the panel data match the real-world causal lags in the process under study (Vaisey & Miles, 2017). However, according to the literature on General Purpose Technologies, there is reason to believe that latency would have a lagged effect on productivity, as it takes time for new technology to affect productivity growth (David 1990; Brynjolfsson & Hitt, 2003).

The findings that the lagged variable is only significant for OECD countries is also of interest. It suggests that it is primarily OECD countries that are able to take advantage of the benefits of lower latency. Figure 2 clearly shows that OECD countries have a much higher IoT concentration, measured as IoT connections per 100 inhabitants, compared to non-OECD countries excluding China. Thus, one possible explanation could be that OECD countries have reached a higher maturity in digitalisation and automation in production processes and thus are able to take advantage of the benefits of lower latency.

These findings also provide some hope for future productivity development. There appear to be continued possibilities of increased productivity by investing in cellular networks and ICT technology. Thus, policy makers in OECD countries should continue to facilitate investment in cellular networks without distorting market competition, which will hopefully lead to better capabilities in the networks and higher productivity in the OECD economies. In contrast, policy makers in non-OECD countries need to establish a further understanding of why the lagged change of latency may not be correlated with productivity growth in their respective economies. Thus, further research is necessary in order to understand why lower latency is not associated with TFP growth in non-OECD countries. Possible explanations might be that non-OECD countries have not made large investments in IoT infrastructure, that additional investment in intangible assets, such as R&D and vocational training, are needed, or simply that the structure of non-OECD countries is completely different from the structure of OECD countries. Based on the findings, policy makers in non-OECD countries should proceed to develop a broadband strategy that best fits their respective economies.

Finally, this paper has extended the analysis of the association between lagged change in latency and TFP growth. An additional area for future research would be to investigate how lower latency improves productivity in different industries and companies. This paper is limited to only establishing that there is a negative association between one-year lag of latency and TFP growth at the country level, but not what is driving this development. Moreover, it remains to be seen how continued investment in mobile infrastructure will affect productivity growth as new use cases and technologies, such as Artificial Intelligence, become available at a large scale.

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Blockchain Technology Adoption Through the UTAUT Model

Exploring the Mediating Role of Trust in Technology

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Abstract: This paper studies the adoption of blockchain technology under the scope of the Unified Theory of Acceptance and Use of Technology (UTAUT). Previous results on Management Information Systems (MIS) research are divergent about the significance of UTAUT variables in explaining the adoption behaviour of blockchain technology. The paper focuses on this specific concern and tries to contribute to existing studies by testing the model in a specific context (Tunisia) and by considering the individual variable "trust in technology" as a mediating one. For this aim, a structural equation approach is adopted among 95 Tunisian professional respondents operating in technology-based sectors. The findings stipulate the importance of facilitating conditions and performance expectancy as drivers of the adoption intention. Additionally, the study reveals that trust in technology is significant in its mediating role in influencing the intention of adoption with the facilitating conditions and the social influence constructs. Moreover, the paper uncovers a direct relationship with the same variable. These findings provide valuable insights for both researchers and practitioners in understanding the factors that influence blockchain technology adoption in the Tunisian context and stress the indirect role of trust in technology with which decision-makers should be concerned.

Keywords: Blockchain technology, UTAUT, behavioural intention, adoption factors, trust in technology

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Introduction

Blockchain technology has emerged as one of the most promising innovations of the 21st century (Alshamsi *et al.*, 2022). Fundamentally designed as a distributed, decentralised ledger, blockchain provides a secure and transparent way to store information without the intervention of a trusted third party (Alshamsi *et al.*, 2022; Ameyaw & deVries, 2023). With its decentralised and immutable architecture, blockchain has the potential to transform entire industries, ranging from finance and logistics to healthcare and governance (Azan *et al.*, 2021). By leveraging concepts such as cryptography and distributed consensus, blockchain is paving the way for new business models and unprecedented collaboration, while preserving data integrity and building trust within networks. As the technology continues to grow in popularity, its impact transcends the limitations of simple digitisation to shape the future of how data is stored, shared and secured globally.

As a consequence of the recognition of its benefits, research on the topic of blockchain adoption has been extensive in recent years (Abed, 2020; Bag *et al.*, 2022), but results are divergent, and there are no common conclusions about theories and applications. Hence, the present paper studies the adoption of blockchain technology under the scope of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003; Venkatesh & Davis, 2000). The authors adopted the UTAUT because it is the best-known model in the management information system (MIS) field (Willams *et al.*, 2015;Ennajeh & Amami, 2014, Sharma *et al.*, 2023).The paper holds a specific theoretical framework to discover the most relevant factors explaining blockchain technology adoption. The choice of the UTAUT aims to identify the individual factors, considered as an important perspective in this context (Alshamsi *et al.*, 2022). However, previous results on MIS research are divergent about the significance of UTAUT variables in explaining the adoption behaviour of blockchain technology in different contexts. The paper focuses on this specific concern and tries to contribute to existing studies by testing the model in a specific context (Tunisia) and by considering the individual variable "trust in technology" as a mediating one.

Consequently, the paper aims to contribute to existing studies by focusing on testing the UTAUT in the Tunisian context. Furthermore, and as suggested by Sharma *et al.* (2023),the UTAUT inspired researchers to make modifications to the original structure of the model. Subsequently, the authors of this paper considered another individual variable, trust in technology, which is regarded as relevant in the case of blockchain technology (Fleischmann & Ivens, 2019).

The choice of trust in the research model is explained by the attributes of blockchain and by the nature of transactions embedded in this peer-to-peer network. The generation of trust is

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seen as one of the greatest advantages associated with blockchain (Fleischmann & Ivens, 2019). Therefore, trust is a key factor that can influence individual behaviour toward the use of blockchain. This idea is also maintained by Batwa & Normann (2021) who assumed that there is a strong relationship between trust and blockchain technology. They added that trust is the main driver for applying blockchain technology.

Furthermore, trust plays a crucial role in accelerating blockchain adoption across diverse industries. Trust serves as a crucial mediator in the widespread adoption of blockchain technology across various industries (Truong *et al.*, 2021).

Consequently, the main objective of this paper is to explain the behavioural intention of using blockchain through the UTAUT. Moreover, it sheds light on the mediating role of trust in technology with the determinants of the UTAUT model. The research questions of the paper are mainly as follows:

- What are the determinants of blockchain technology adoption in the Tunisian context?
- How does trust in technology mediate the relationship between the UTAUT variables and the behavioural intention of using blockchain technology?

To answer research questions and validate theoretical constructs, partial least squares structural equation modelling (PLS-SEM) (Hair Jr *et al.*, 2017) was performed. Data was collected from 95 Tunisian professionals operating in technology-based sectors in Tunisia.

As an outline, the rest of the paper presents a literature review of blockchain technology and its adoption. The second section concerns the theoretical foundations (UTAUT model and trust in blockchain). The third section aims to build the theoretical model and the hypothesis. The fourth section is dedicated to the presentation of the methodology and the research design. The fifth section presents a discussion of the results. Finally, the conclusion summarises the paper's contributions.

Literature Review

Introducing blockchain technology

Blockchain, as an emerging innovation in the digital economy, is supposed to transform traditional business models and reshape socio-economic dynamics. Its growing adoption globally is fuelled by both the vertical expansion of its adoption rate and the horizontal increase in the number of available blockchain applications (Ennajeh, 2021). This revolutionary technology operates within a network that brings together actors who want to exchange assets directly, without third parties or central authorities. It makes it easier to keep information in public records, accessible to all members of the network, where data is immutably recorded. Blockchain has the potential to build trust, transparency, security and visibility between partners (Golosova & Romanovs, 2018).

More technically, blockchain is defined as distributed ledger technology (DLT), which is a protocol allowing data exchange between network partners without intermediaries, such as third-party logistics (Jraisat *et al.*, 2021; Mohammed *et al.*, 2021).

Tapscott & Tapscott (2017) conceived the well-known definition of blockchain: *"An incorruptible digital ledger of economic transaction that can be programmed to record not just financial transactions but virtually everything of value.*"

Originally, blockchain technology was created as the technology that supports Bitcoin (Nakamoto, 2008). Later, blockchain surpassed cryptocurrencies and financial services; it was expected to revolutionise many other sectors (Woodside *et al*, 2017). In fact, blockchain technology evolution has undergone three stages: first, Blockchain 1.0 where the deployment of cryptocurrencies as a peer-to-peer cash payment system emerged. Second, Blockchain 2.0, the more extensive blockchain application, includes bonds, loans, smart property and smart contacts. Third, Blockchain 3.0, which is characterised by the development of blockchain applications in the areas of government, health, science, literacy, culture and art (Alshamsi *et al.*, 2022).

Blockchain applications are explored and adopted in many economic sectors with different adoption rates, including healthcare, finance and banking, education, governance, supply chain, energy and agriculture (Ennajeh, 2023).

Blockchain technology adoption

Demand for blockchain applications is growing rapidly in various industries. Statistics published by Ruby (2023) demonstrate an annual growth of the blockchain industry of about 56.3%. The evolution of blockchain technology in terms of adoption rate and application development inspired questions to understand its actual and future use.

In the MIS field, studies about technology or innovation adoption comprise some of the most robust areas, and their major preoccupation is to explain the adoption behaviour predicted by individuals' or organisations' intentions to adopt innovation. Generally, the adoption is influenced by several factors related to the individual perception of the usefulness of new technology in the organisational context.

The exponential growth of blockchain technology applications calls for studies to understand its adoption. Literature on blockchain technology adoption has also grown in recent years and demonstrates that the blockchain system has not yet reached the maturity stage and that extensive studies should be conducted before implementation (Wang *et al*., 2016; Janssena *et al*., 2020).

According to Alshamsi *et al.* (2022), the technology acceptance model (TAM), technology organisation and environment (TOE), UTAUT and Innovation Diffusion Theory (IDT) are the models most widely used to understand blockchain technology adoption.

The study of Queiroz *et al.* (2021), for example, investigated blockchain technology adoption behaviour by drawing a model of UTAUT. The proposed model was validated in Brazilian operations and supply chain professionals. Results demonstrated that facilitating conditions, trust, social influence, and effort expectancy are the most critical constructs that directly affect blockchain adoption. However, performance expectancy was not decisive.

Khazaei (2020) also tested an extended version of UTAUT in a Malaysian context. The author added personal innovativeness, security, technology awareness and trust to the original constructs of the underlined model. Findings show that only technology awareness was not significant in its impact on adoption intention.

Furthermore, Kabir *et al.* (2021) investigated determinants of blockchain acceptance in the context of the Bangladeshi financing supply chain by testing the UTAUT model with direct and indirect relation. The results supported the original model relationships except for social influence. The mediating role of behavioural intention to use blockchain between facilitating conditions and the actual use of blockchain is also supported.

As a conclusion to the literature review, research on blockchain adoption has increased in recent years but results are not always the same given the difference in studied context, the nature of blockchain applications and the economic activity of adopters. Thus, previous findings call for substantially more investigations on determinants of blockchain adoption.

Theoretical Foundations

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT is a unified theory that gathers all theories advanced previously to the study of Venkatesh *et al.* (2003). The founders of UTAUT examined constructs of the theory of reasoned action (TRA) (Azjen & Fishbein, 1980), the social cognitive theory (SCT) (Bandura, 1986), the theory of planned behaviour (TPB) (Azjen, 1991), the model of personal computer use (MPCU) (Thompson *et al*., 1991), the model of technology acceptance(TAM and TAM2) (Davis *et al*., 1989;Venkatesh & Davis, 2000), the motivational model (MM) (Davis *et al*., 1992), the combined TAM-TPB theory (Taylor & Todd, 1995), and the diffusion of innovation theory (DOI) (Rogers, 1995). UTAUT authors have an objective to test all constructs proposed and tested in those theories to formulate a unique view that can explain adoption behaviour through the influence of individual intention to adopt any technology or innovation. Constructs deduced to build the original UTAUT model are *performance expectancy, effort expectancy, social influence, and facilitating conditions*. Moderator variables were also added and tested (age, gender, experience and voluntary use) (Venkatesh *et al*, 2003).

The UTAUT is one of the most frequently used models for researching technology acceptance (Wong *et al.*, 2020). According to Google Scholar citations, the paper of Venkatesh *et al.* (2003) was cited 47,957 times until 2023.As a result, the purpose of this work is to add to the current literature by evaluating the UTAUT model in the context of blockchain technology and providing data that may be useful for future research.

Trust and blockchain technology

Trust as a construct in management science was first introduced and defined by Rousseau *et al.* (1998, p. 395) as a "*psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behaviour of another*".

The specific construct of trust in technology was created and defined by Mcknight *et al.* (2011). In their study, the authors argued that "*trust in a specific technology refers to a person's relationship with a particular technology*" (Mcknight *et al.*, 2011, p. 6). They added that trust in technology is more palatable to apply than the interpersonal trust constructs used in previous studies.

In the context of blockchain technology, trust in general and trust in technology in particular were studied by many researchers(Fleischmann & Ivens, 2019; Chawla, 2020; Jardim *et al.* 2021). This is explained by the attributes of the technology itself and by the nature of transactions embedded in this peer-to-peer network. Fleischmann & Ivens (2019) argued that the generation of trust is regarded as one of the greatest advantages associated with nascent blockchain applications.

According to Chawla (2020), the nature of trust in blockchain differs from its traditional view in organisations. In fact, he indicated that trust in blockchain embodies algorithmic and organisational trust.

Following this idea, Fleischmann & Ivens (2019) underlined the crucial role of trust due to technical design features of blockchain technology and applications. Further, blockchain technology can create a level of trust in the digital world that even reputable market players are not able to do.

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Theoretical Constructs and Model Building

As mentioned earlier, this paper intends to test the relevance of the UTAUT (Venkatesh *et al*, 2003) when explaining the intention to adopt blockchain technology. Given the novelty of this technology and its limited use in the Tunisian context, the analysis will be limited to studying the intention behaviour. The basic idea of the model is that an individual's intention to adopt blockchain technology is influenced by personal judgement about some determinants of innovation. According to the UTAUT model, those factors are as follows.

Performance expectancy

In their study, Venkatesh *et al.* (2003) defined performance expectancy as a measure of a person's belief in improving their job performance using a new system. Therefore, using a new system or technology to perform tasks can be perceived as offering many benefits (Khazaei, 2020). Performance expectancy can thus be seen as an important indicator of intention to adopt blockchain technology; a finding in line with previous research on the adoption of blockchain technology in various contexts (Khazaei, 2020; Queiroz *et al.*, 2021; Wong *et al.*, 2020; Alazab *et al.*, 2021;Kabir *et al.*, 2021).

Consequently, an individual's intention to adopt blockchain technology is related to the perceived advantages of a particular job. Subsequently, the following hypothesis is advanced:

> *H1: Performance expectancy has a positive impact on behavioural intention to use blockchain technology.*

Effort expectancy

Corresponding to research by Venkatesh *et al.* (2003), effort expectancy describes the perceived complexity or difficulty associated with using a new system. This expectancy of effort is critically important when an individual perceives the ease of learning and using technology. More recently, definitions have expanded on the original definition by emphasising that this variable measures the ease of use of a new technology. In the specific context of blockchain technology, many previous studies agree that effort expectation is a strong predictor of its adoption (Kabir *et al.*, 2021; Wong *et al.*, 2020; Khazaei, 2020; Queiroz *et al.*, 2021). In other words, if future users perceive blockchain technology as simple to use, it will entice them to adopt it (Kabir *et al.*, 2021).

As a result, we hypothesise as follows:

> *H2: Effort expectancy has a positive impact on behavioural intention to use blockchain technology.*

Social influence

Social influence encompasses the assessment of the degree of influence exerted by various actors, such as colleagues, family, friends, partners, and peers, on individual intention to adopt a technology. In the specific context of blockchain technology, Khazaei (2020) argued that social influence is of crucial importance due to the community-based nature of this technology. In addition, a lot of previous research has corroborated the findings regarding the impact of social influence on behavioural intention to adopt blockchain (Kabir *et al.*, 2021; Alazab *et al.*, 2021; Wamba & Queiroz, 2019; Khazaei, 2020).

As a result, at this stage of the analysis we make the following assumption:

> *H3: Social influence has a positive impact on behavioural intention to use blockchain technology.*

Facilitating conditions

The construct of facilitating conditions, as introduced by Venkatesh *et al.* (2003), refers to the organisational and technical infrastructure put in place by an organisation to encourage the adoption of a new system. According to Wong *et al.* (2020), these enabling conditions refer to the user's perception of resources and support that facilitate the adoption of new technologies. In the specific context of blockchain technology, the company must offer technical support, software and hardware equipment, as well as in-depth knowledge of the system, as highlighted by Queiroz & Fosso Wamba (2019). The successful integration of blockchain technology into existing infrastructure is essential, as mentioned by Wong *et al.* (2020). Therefore, facilitating conditions exerts a significant influence on blockchain adoption. As a result, the following hypothesis is formulated:

> *H4: Facilitating conditions has a positive impact on behavioural intention to use blockchain technology.*

The original UTAUT model considers age, gender, voluntariness and experience as moderators of the relationship between adoption factors and behavioural intention to use a technology. In the present study, those moderators were not integrated like recent applications of the UTAUT such as in the studies of Wong *et al.* (2020) and Queiroz *et al.* (2021).

The mediation role of trust in technology

In the field of information systems, trust plays a crucial role as a key predictor of technology adoption and is a key determinant of how users perceive technology (Li *et al.*, 2008; McKnight *et al.*, 2011). One of the key factors influencing the adoption of any technology is the level of trust that users have in its capabilities. Trust is a vital aspect in technology adoption as it influences users' attitudes, perceptions and intentions towards using new technology (Momani, 2020). Perceived trust is a complex and multifaceted phenomenon that significantly impacts corporate relationships. In addition to people, technology is also trusted, which can alter people's behaviour and decision-making about its use (Chawla *et al.*, 2023).

In the case of blockchain technology, trust is guaranteed by the technology itself, given the level of security associated with transactions and exchanges in this chain (Queiroz *et al.*, 2021). Jardim *et al.* (2021) have claimed that the acceptance of technology such as blockchain depends on trust levels.

The suggested model is an extension of UTAUT by adding the mediating role of trust in technology. As discussed above, trust in technology has the potential to influence the individual's perceptions and then the acceptance of blockchain. Subsequently, the following main hypotheses can be introduced:

> *H5: Trust in technology mediates the relationship between UTAUT constructs and behavioural intention to adopt blockchain.*
>
> *H5a: Trust in technology mediates the relationship between facilitating conditions and behavioural intention to use blockchain technology.*
>
> *H5b: Trust in technology mediates the relationship between social influence and behavioural intention to use blockchain technology.*
>
> *H5c: Trust in technology mediates the relationship between effort expectancy and behavioural intention to use blockchain technology.*
>
> *H5d: Trust in technology mediates the relationship between performance expectancy and behavioural intention to use blockchain technology.*

In addition to its mediation role, the paper intends to test the direct relation between trust in technology and behavioural intention to adopt blockchain technology. For this reason, the following hypothesis is introduced:

> *H6: Trust in technology has a positive impact on behavioural intention to use blockchain.*

The final structure of the conceptual model is presented in Figure 1.

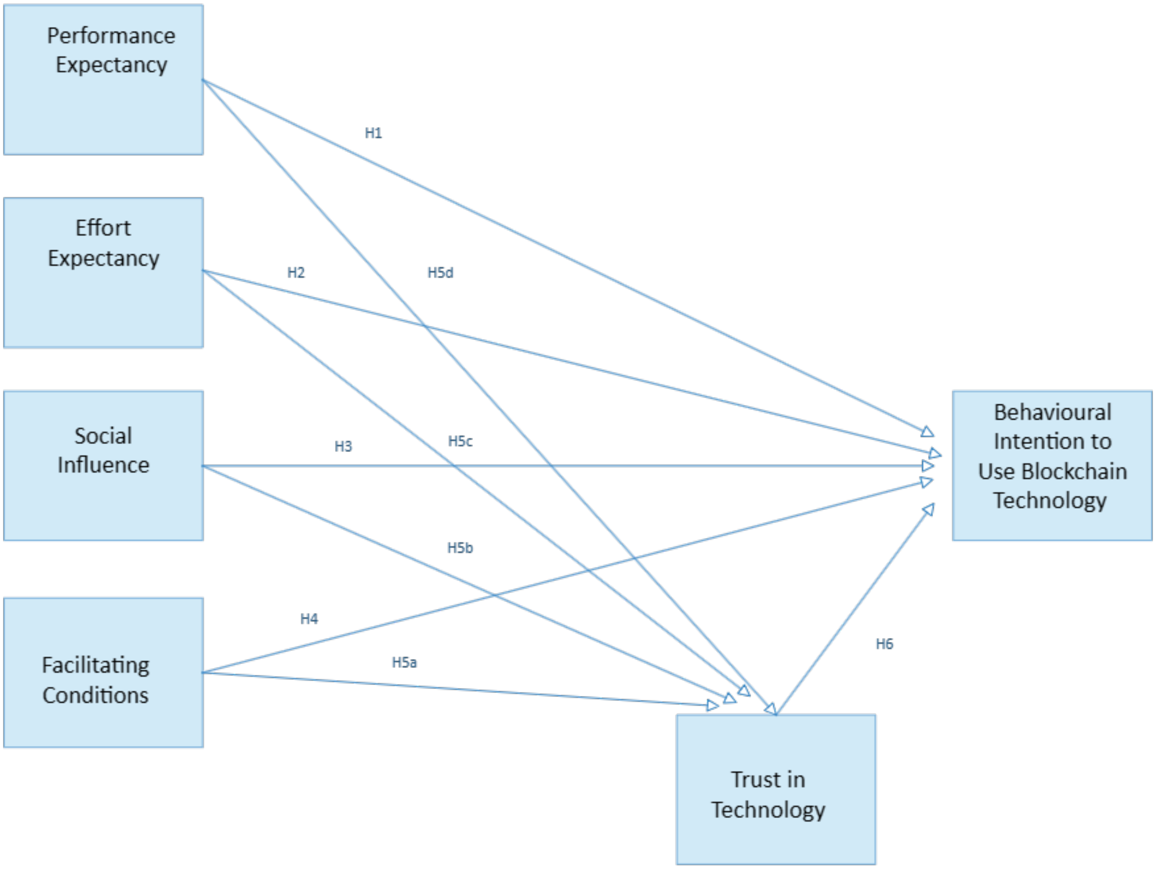

Figure 1. Extended UTAUT model explaining behavioural intention to adopt blockchain technology

Research Methodology Design

PLS (partial least squares) is a statistical method commonly used in social sciences and business research to analyse relationships between variables. Additionally, PLS is advantageous because it can cope with small sample sizes and does not rely on the assumption of normally distributed data.

The design of the research respects a set of stages. As a first step, authors pre-selected the respondents, intending to validate the selection criteria. Professionals chosen are in technology-based sectors and who deal with acceptable levels of technical tasks in their positions. The confirmatory phase of the model is assisted by the IBM-SPSS statistics. The principal analysis and the reliability of the items are well performed by the same program.

Additionally, the researchers conducted a pilot study to ensure the validity and reliability of the survey instrument. This helped identify any potential issues or areas for improvement before administering the survey to a larger sample. The data collected from the survey was then analysed using various statistical techniques to evaluate the hypotheses and draw meaningful conclusions.

We sought respondents who regularly accomplish their tasks through technology and who have a high level of technical knowledge. The distribution of the questionnaire is presumed as being the last step before the analysis and the verification of the hypothesis. The collected questionnaires reached 95 respondents from Tunisia.

Sample and participants

The 95 respondents consist of 39 women (41.1%) and 56 men (58.9%). The sample presents 59 technical respondents. Most respondents are between 26 and 45 years old (77.9%). Moreover, based on the selection criteria of the respondents, the implication of the technology used was relevant to choosing them. Hence, the sample presents 85.3% of people who are implicated in the technology acquisition process (recommendation and decision-making). In the same fashion, 63.2% of them are conscious of the incidence and the impact of blockchain technology on the functions of their companies.

Measures

A four-item measure created by Venkatesh & Zhang (2010) and Venkatesh *et al.* (2003) was used to evaluate respondents' behavioural intentions. The four items used in this article to evaluate performance expectation are Pexp1 and Pexp2 from Venkatesh *et al.* (2003), Pexp3 from Wong *et al.* (2020), and Pexp4 from Mearian (2018). We employed the Venkatesh *et al.* (2003) four-scale items for effort expectations. Based on the scale from Queiroz *et al.* (2021), social influence was evaluated.

The table in Appendix A provides the operationalisation of several ideas associated with our study, assessed using a five-point Likert scale. The Venkatesh *et al.* (2003) scale was used to quantify the facilitating conditions, while trust was assessed using the scale from Ooi & Tan (2016) and Slade *et al.* (2015). All variables demonstrated high internal consistency, with alpha values greater than 0.8. The operationalisation of the items associated with our study is shown in the Appendix.

Research Results

Test of the measurement model

As shown in Figure 1, reflective structures make up the research model. We tested the reflective constructs' validity and reliability, which are divided into three stages (Chin, 1998): discriminant validity, convergent validity, and reliability.

These stages of testing ensure that the reflective constructs used in the research model are reliable and valid. As shown in Table 1, the results indicate that the composite reliability and Cronbach's alpha values meet the established thresholds for dependability.

Additionally, the average variance extracted (AVE) for each latent variable was found to be above 0.5, as recommended by Fornell & Larcker (1981) (Table 1).

Table 1. Reliability and validity of the constructs

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
Behavioural intention to use blockchain technology	0.874	0.876	0.914	0.728
Effort expectancy	0.916	0.930	0.941	0.799
Facilitating conditions	0.913	0.923	0.939	0.796
Performance expectancy	0.915	0.916	0.940	0.797
Social influence	0.888	0.894	0.930	0.817
Trust in technology	0.905	0.918	0.933	0.739

In this study, the outer loadings of the measurement items for all latent variables exceeded the threshold of 0.7, indicating good convergent validity (see Appendix C). It is important to mention that the item TRS5 has the value of 0.595 in the outer loading with its construct. We decided to preserve it, since the elimination of items is considered to be a crucial decision in keeping the acceptable level of prediction.

Table 2. Fornell–Larcker criteria for discriminant validity of the constructs

	Behavioural intention to use blockchain technology	Effort expectancy	Facilitating conditions	Performance expectancy	Social influence	Trust in technology
Behavioural intention to use blockchain technology	0.853					
Effort expectancy	0.524	0.894				
Facilitating conditions	0.777	0.594	0.892			
Performance expectancy	0.617	0.579	0.532	0.893		
Social influence	0.720	0.687	0.892	0.568	0.904	
Trust in technology	0.785	0.618	0.852	0.488	0.840	0.860

The Fornell–Larcker criteria are used to assess discriminant validity, which requires that the square root of each construct's AVE should be higher than its correlations with other

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constructs. By applying this test, the study confirms that the latent variables in Table 3exhibit discriminant validity.

Additionally, Hair *et al.* (2017) test discriminant validity in PLS-SEM using the heterotrait–monotrait ratio (HTMT) criteria. For any pattern of build, the HTMT statistics' confidence interval should not include the value 1 (Table 3).

This indicates that the constructs in the study have discriminant validity, meaning they measure distinct concepts and are not redundant or repetitive. The HTMT criteria provide a reliable method for assessing discriminant validity in PLS-SEM.

Table 3. Heterotrait–monotrait ratio (HTMT) discriminant validity of constructs

	Behavioural intention to use blockchain technology	**Effort expectancy**	**Facilitating conditions**	**Performance expectancy**	**Social influence**	**Trust in technology**
Behavioural intention to use blockchain technology						
Effort expectancy	0.581					
Facilitating conditions	0.864	0.653				
Performance expectancy	0.691	0.629	0.587			
Social influence	0.807	0.756	0.993	0.625		
Trust in technology	0.884	0.683	0.931	0.553	0.930	

Test of hypotheses of the structural model

The coefficient of determination (R2), which expresses the strength of the relationship between the independent and dependent variables, is used to evaluate the model's quality. The R2 values are 71.6% and 76.3% respectively for the intention behaviour of using blockchain technology and for trust in technology, which indicates a high-quality model.

To evaluate the impact's importance, the coefficient's value is insufficient. To determine if the route coefficients are relevant, the t-test is the suitable method (see Table 5).

The t-test allows us to assess the statistical significance of the coefficients in determining the impact's importance. By comparing the t-values to critical values, we can determine if the coefficients are statistically significant or not. This helps us determine if the route coefficients have a meaningful impact on the outcome variable.

Table 4. t-test of the path coefficients after bootstrapping (resampling: 5000)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics(|O/ STDEV|)	P values
Effort expectancy -> behavioural intention to use blockchain technology	-0.078	-0.066	0.093	0.834	0.405
Effort Expectancy -> Trust in technology	0.109	0.108	0.075	1.453	0.146
Facilitating conditions -> behavioural intention to use blockchain technology	0.371	0.390	0.167	2.219	0.027
Facilitating conditions -> Trust in technology	0.520	0.527	0.136	3.823	0.000
Performance expectancy -> behavioural intention to use blockchain technology	0.307	0.307	0.081	3.779	0.000
Performance expectancy -> Trust in technology	-0.033	-0.029	0.070	0.475	0.635
Social influence -> behavioural intention to use blockchain technology	-0.136	-0.142	0.166	0.820	0.412
Social influence -> Trust in technology	0.320	0.310	0.117	2.731	0.006
Trust in technology ->behavioural intention to use blockchain technology	0.481	0.459	0.139	3.466	0.001

We have evaluated the structural model's output after verifying the validity and reliability of our constructs (Table 1). This entails analysing the crucial parameters, including the path coefficient's magnitude, sign, and significance as well as the R2 value (Hair *et al.*, 2017).

As a first step, the test of the direct relations is performed (Table 5). Additionally, we will also examine the mediating effect of trust in technology on the relationship between behavioural intention to use blockchain technology and the four latent variables in our model (Table 6). This analysis allows us to gain a deeper understanding of the indirect impact of trust in technology on the adoption of blockchain technology. As an outline, based on the significance of the path coefficients, the paper confirms the validation of the following direct relations; H1, H4, and H6.

Test of the mediation effect

Direct effects refer to the relationship between two constructs that are not influenced by any other variables. On the other hand, indirect effects occur when there is an intervening variable that mediates the relationship between the two constructs (Hair *et al.*, 2017). These indirect effects can involve a series of interactions with multiple intervening variables, further complicating the understanding of the underlying mechanism or process.

"*To test the mediation relations, researchers should bootstrap the sampling distribution of the indirect effect*" (Hair *et al.*, 2017). As a result, the mediating effect's choice considers the importance of both the direct and indirect effects.

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The concept of partial mediation suggests that the mediator construct only partially explains the relationship between the two latent variables, leaving a place for other factors to influence the connection. On the other hand, complete mediation (full mediation) implies that the mediator construct fully accounts for the observed relationship between the variables, with no additional factors playing a role. The methodology used by Zhao *et al.* (2010) is valuable in understanding and identifying these diverse types of mediation effects.

The authors of this paper advise examining the bootstrapped distribution's confidence interval if there are discrepancies between the estimated indirect impact and the mean of the bootstrapped distribution. The bootstrap confidence interval, in fact, "*provides an estimated range of values that is likely to include an unknown population parameter*," according to Hair *et al.* (2017).Confidence intervals are commonly used in statistical analysis to provide a measure of uncertainty and to assess the precision of an estimated parameter.

Based on the work of Zhao *et al.* (2010), the study of the indirect relations of the model was assessed. The results are presented in the following table.

Table 5. Test of the indirect effect after bootstrapping (resampling: 5000)

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.5%	97.5%	Signific-ance (p<0.05)
Total effect							
Performance expectancy -> behavioural intention to use blockchain technology	0.291	0.294	3.361	0.001	0.123	0.462	YES
Effort expectancy -> behavioural intention to use blockchain technology	-0.025	-0.018	0.247	0.805	-0.206	0.194	NO
Social influence -> behavioural intention to use blockchain technology	0.018	0.006	0.099	0.921	-0.351	0.346	NO
Facilitating conditions -> behavioural intention to use blockchain technology	0.621	0.625	3.778	0.000	0.305	0.939	YES

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	Original sample (O)	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**2.5%**	**97.5%**	**Signific-ance (p<0.05)**
Direct effect							
Facilitating conditions -> behavioural intention to use blockchain technology	0.621	0.625	2.219	0.027	0.296	0.929	YES
Facilitating conditions -> trust in technology	0.520	0.527	3.823	0.000	0.236	0.773	YES
Social influence ->behavioural intention to use blockchain technology	0.018	0.006	0.820	0.412	-0.335	0.359	NO
Social influence -> trust in technology	0.320	0.310	2.731	0.006	0.095	0.558	YES
Effort expectancy -> behavioural intention to use blockchain technology	-0.025	-0.018	0.834	0.405	-0.209	0.187	NO
Effort expectancy -> trust in technology	0.109	0.108	1.453	0.146	-0.027	0.275	NO
Performance expectancy -> behavioural intention to use blockchain technology	0.291	0.294	3.779	0.000	0.109	0.450	YES
Performance expectancy -> trust in technology	-0.033	-0.029	0.475	0.635	-0.164	0.112	NO
Trust in technology ->behavioural intention to use blockchain technology	0.481	0.459	3.466	0.001	0.203	0.730	YES

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.5%	97.5%	Signific-ance ($p<0.05$)
Indirect effect							
Facilitating conditions -> trust in technology -> behavioural intention to use blockchain technology	0.250	β=0.236	2.974	0.003	0.114	0.458	YES
Social influence -> trust in technology -> behavioural intention to use blockchain technology	0.154	β=0.149	1.892	0.050	0.033	0.368	YES
Effort expectancy -> trust in technology -> behavioural intention to use blockchain technology	0.053	β=0.048	1.438	0.151	-0.002	0.146	NO
Performance expectancy -> trust in technology -> behavioural intention to use blockchain technology	-0.016	β=-0.013	0.469	0.639	-0.094	0.047	NO

Referring to Table 5, the findings on mediation and confidence intervals demonstrate the verification of certain hypotheses (see Table 6). Specifically, two indirect effects of the mediating variables were found to be significant (through social influence and facilitating conditions), while the other two were not (through performance expectancy and effort expectancy). Regarding the direct impact of UTAUT determinants on the intention to adopt blockchain technology, the results highlight the importance of performance expectancy and facilitating conditions.

Moreover, the direct relationship between trust in technology and the intention to use is presumed to be significant. The former citations disclose the full mediation and the complementary mediation of the social influence and facilitating conditions constructs (Zhao *et al.*, 2010). However, the two other constructs (performance expectancy and effort expectancy) did not show mediation relations with the trust in technology and the adoption of blockchain technology.

As a summary, Table5 demonstrates that the intention of using blockchain technology is positively influenced by the social influence through the construct of trust in technology:

$$\beta = 0.149, p = 0.050, CI [0.033; 0.368]$$

Concerning the facilitating conditions, the mediation is partial (complementary) with

$$\beta = 0.236, p = 0.003, CI [0.114; 0.458]$$

However, the construct performance expectancy has no mediation through trust in technology (only direct relation):

$$\beta = -0.013, p = 0.639, CI [-0.094; 0.047]$$

And the same result for the construct effort expectancy where no mediation is founded:

$$\beta = 0.048, p = 0.151, CI [-0.002; 0.146].$$

Table 6 displays the verification of the research hypotheses.

Table 6. Verification of the hypothesis

Hypothesis	Validation/rejection
H1: Performance expectancy has positive impact on behavioural intention to use blockchain technology.	Validated
H2: Effort expectancy has a positive impact on behavioural intention to use blockchain technology.	Rejected
H3: Social influence has a positive impact on behavioural intention to use blockchain technology.	Rejected
H4: Facilitating conditions have a positive impact on behavioural intention to use blockchain technology.	Validated
H5: Trust in technology mediates the relation between UTAUT constructs and behavioural intention to adopt blockchain technology.	Partially validated
H5a: Trust in technology mediates the relation between facilitating conditions and behavioural intention to use blockchain technology.	Validated. complementary (partial mediation)
H5b: Trust in technology mediates the relation between social influence and behavioural intention to use blockchain technology.	Validated complete mediation (full mediation)
H5c: Trust in technology mediates the relation between effort expectancy and behavioural intention to use blockchain technology.	Rejected (no mediation)
H5d: Trust in technology mediates the relation between performance expectancy and behavioural intention to use blockchain technology.	Rejected: only direct effect (no mediation)
H6: Trust in technology has a positive impact on behavioural intention to use blockchain technology.	Validated

Discussion of Results

Findings of the present study demonstrate the significance of performance expectancy (structural coefficient = 0.302) and facilitating conditions (structural coefficient = 0.371) on explaining the intention to adopt blockchain technology. In addition, trust in technology seems to have the greatest impact on behavioural intention (0.481). Subsequently, the recommended model explains 71% of the behavioural intention to use blockchain technology by individuals in an organisational context.

The results of trust and facilitating conditions are consistent with the study of Queiroz *et al.* (2021). However, the significance of effort expectancy and performance expectancy diverge from the results of Queiroz *et al.* (2021).

The systematic literature review of Alshamsi *et al.* (2022) found that social influence is one of the most determinant factors of blockchain technology adoption. The result of the present study about social influence is not in line with previous ones.

This finding is, then, appropriate to the Tunisian context and for Tunisian professionals. Highly skilled people (respondents) understand blockchain technology more than people around them. Consequently, they are not influenced by colleagues' or friends' opinions.

To summarise, the results of full UTAUT constructs were significant in the studies of Khazaei (2020) and Kabir *et al.* (2021), which is not consistent with the findings of the present study where only two constructs of the model are significant. Managers and practitioners involved in blockchain projects need to consider the particularities of the contexts, showing that there are meaningful differences between countries in blockchain adoption (Wamba & Queiroz, 2019).

Concerning the mediation relation of trust in technology, a full mediation and a partial one are verified with the facilitating conditions and the social influence. The main contribution of the present study is adding trust to the UTAUT original model. Results show the relevance of trust construct in the case of blockchain technology. The direct impact on behavioural intention is maintained by previous studies. For example, Fleischmann & Ivens (2019) discovered that trust has been identified as one of the key drivers of acceptance of technology in the digital context. They added that trust acts like an antecedent of usage behaviour "*by establishing confident expectations about the system, and as an antecedent of controllability, by reducing uncertainty*" (Fleischmann & Ivens, 2019).

Results of the present study are consistent with this idea because of the direct relationship found between trust and facilitating conditions on one hand, and trust and the social influence on the other hand.

As Chawla (2020) assumed: "*Blockchains are often assumed to be trust-free, or to distribute trust, since their design is unique from the perspective of traditional organisational theories*" (2020, p. 4).

Trust in technology, as advanced in this paper, reflects the trust that individuals have in blockchain technology. The mediating role of trust explains how individual perception of blockchain adoption factors (effort expectancy, performance expectancy, facilitating conditions and social influence) could impact trust in technology and then influence the intention to adopt it. Empirical results demonstrated that trust in blockchain is impacted only by facilitating conditions and social influence. These findings result in relevant practical insights because they identify determinants of trust toward the use of blockchain and, subsequently, its adoption in organisations. Thus, managers should provide the required infrastructure (resources, expertise and knowledge) to implement blockchain technology. By doing this, managers guarantee ideal technological and social climates that have a significant impact in influencing individual intention to use blockchain.

The construct of facilitating conditions seems the more critical one in the Tunisian context (the context of the study) because of its direct influence on the behavioural intention to use blockchain and its impact on trust in technology. The relevance of this construct was supported by previous studies (Queiroz *et al.*, 2021; Wong *et al.*, 2020; Queiroz & Wamba, 2019; Kabir *et al.*, 2021).

Understanding factors influencing blockchain adoption intention through MIS theories would help researchers and managers prepare procedures and strategies to encourage the adoption and integration of blockchain technologies across various economic sectors, especially in developing economies like Tunisia. The resulting model of this study can be used by governments, organisations and start-ups to better understand what encourages people to adopt blockchain technology.

Conclusion

The current study tried to uncover the elements that promote blockchain adoption, providing practitioners and decision-makers with relevant information. Organisations may make informed decisions about integrating blockchain technology and optimising their operations if they understand these drivers. Additionally, bridging research gaps in this area might lead to a better understanding of blockchain acceptability and its potential influence on organisational growth. The findings of the research demonstrated the direct effect of performance expectancy and the facilitating conditions. Also, the indirect effect of trust in technology is partially verified regarding the UTAUT determinants.

The research presents theoretical and contextual contributions. On the theoretical side, the research has drawn on the UTAUT model with a special focus on the variable trust in technology. In fact, the mediating role of the said variable is relevant to blockchain adoption.

This statement confirms the existing literature about the importance of trust in projects of blockchain implementation.

On the contextual side, the research is an attempt to validate the UTAUT model of the intention of blockchain use in the Tunisian context. Tunisia has actively embraced the implementation of these technologies, recognising their ability to streamline processes and improve efficiency in various sectors. Even though the government has been supportive of initiatives that promote the adoption of blockchain technology, encouraging collaboration between public and private entities to explore its potential applications further, it has extensively invested in research and development to ensure the continuous advancement of blockchain technology and its effective application.

There are several limitations that should be specifically highlighted to establish the validity of the model's findings. First, the sample could limit the generalisation of the study results at two levels. Second the sample size influences the representativeness of the population. Second, respondents' profiles are also limited to highly skilled individuals, which can influence the significance of technology-related factors such as effort expectancy and performance expectancy.

The authors note that it is imperative to conduct an evaluation using a sizable and diverse sample including various profiles and contexts, such as in the French context.

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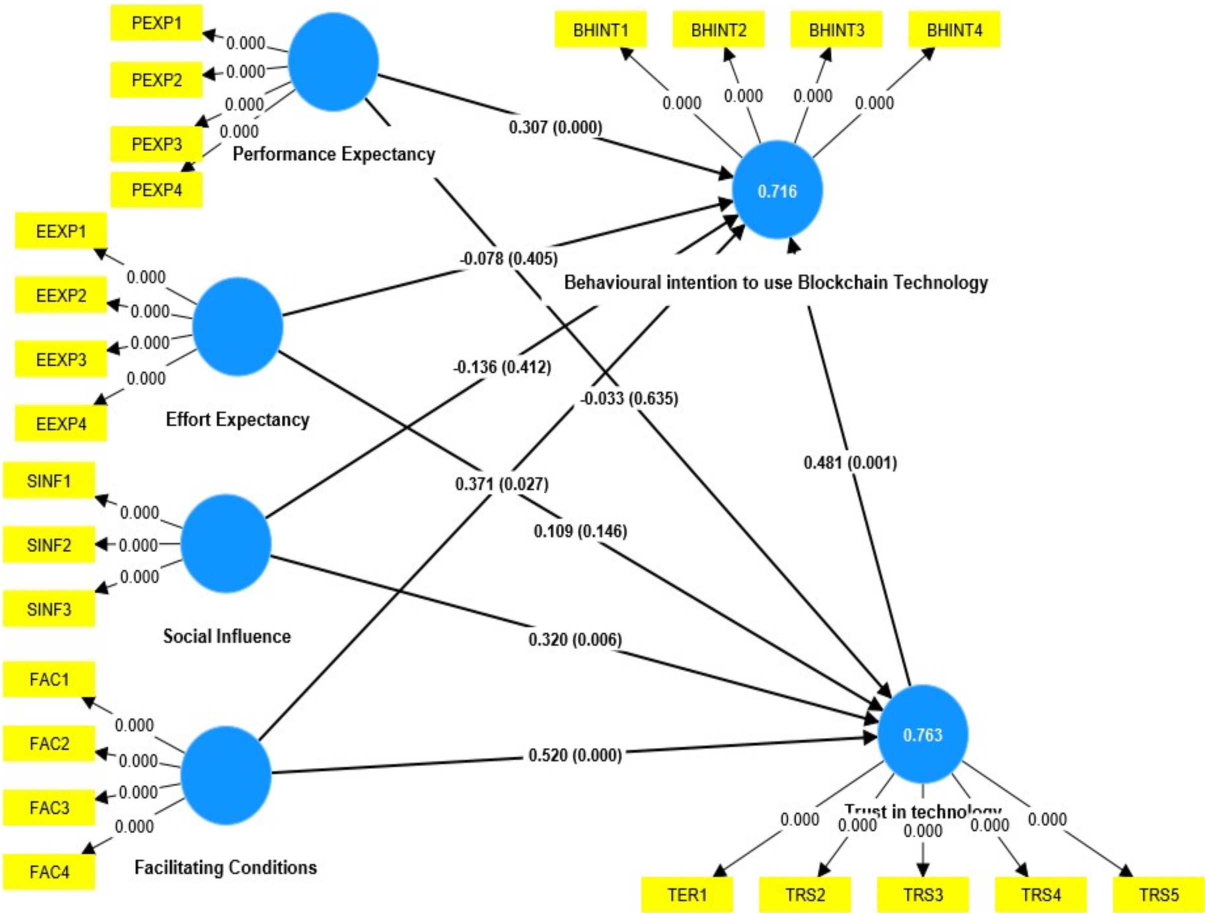
Appendix A: Construct Items

Concept	Items
Behavioural intention Adapted from Venkatesh *et al.* (2003); Venkatesh & Zhang (2010)	**BHINT1** I intend to adopt BC within 3 years **BHINT2** I predict my firm will move into BC within 3 years **BHINT3** My firm is amongst the pioneers to explore BC **BHINT4**My firm intends to digitally transform supply chain management
Performance expectancy Adapted from Venkatesh *et al.* (2003) (1.2); Wong *et al.* (2015) (3); Mearian (2018)	**PEXP1**Using BC enables me to accomplish my tracking tasks more efficiently and effectively **PEXP2**Using BC saves my time and eliminates processing costs by offering all parties a single source view of master ledger **PEXP3**Using BC increases the quality of my work through the use of smart contracts **PEXP4**Using BC can improve financial liquidity because once all parties agree on the delivery of goods, payments can be issued since everyone sees the same record updated in real-time
Effort expectancy Venkatesh *et al.* (2003), Venkatesh, Thong & Xu (2012)	**EEXP1** Learning how to use blockchain is easy for me **EEXP2** My interaction with blockchain is clear and understandable **EEXP3** I find blockchain easy to use **EEXP4** It is easy for me to become skilful in using blockchain
Social influence Queiroz *et al.* (2021)	**SINF1** People who are important to me think that I should use blockchain **SINF2** People who influence my behaviour think that I should use blockchain **SINF3** People whose opinions I value prefer that I use blockchain
Facilitating conditions Adapted from Venkatesh *et al.* (2003)	**FAC1**My firm has the right resources for BC **FAC2**My firm has the expertise for BC in case technical assistance is required **FAC3**My firm has the knowledge necessary for operating BC **FAC4**The management has expressed interest in BC
Trust in technology Adapted from Ooi & Tan (2016); Slade *et al.* (2015)	**TRS1** I have confidence in the use of BC **TRS2** I believe BC can keep the data secure and less prone to fraud **TRS3** I believe I am able to operate BC reliably or consistently without failing **TRS4** I am willing to depend on BC across a broad spectrum of situations and technologies in my work. **TRS5**I believe that BC will consistently operate, providing adequate and efficient results at work

Appendix B: Smart Pls Output After Bootstrapping (Sample:5000)



Appendix C: The Loadings of the Items

	Behavioural intention to use blockchain technology	**Effort expectancy**	**Facilitating conditions**	**Performance expectancy**	**Social influence**	**Trust in technology**
BHINT1	0.829					
BHINT2	0.935					
BHINT3	0.835					
BHINT4	0.807					
EEXP1		0.846				
EEXP2		0.923				
EEXP3		0.937				
EEXP4		0.867				
FAC1			0.783			
FAC2			0.921			
FAC3			0.926			
FAC4			0.930			
PEXP1				0.920		
PEXP2				0.894		
PEXP3				0.886		
PEXP4				0.870		
SINF1					0.867	
SINF2					0.917	
SINF3					0.926	
TRS1						0.924
TRS2						0.920
TRS3						0.890
TRS4						0.922
TRS5						0.595

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Perception of Gen Z Customers towards Chatbots as Service Agents

A Qualitative Study in the Indian Context

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Abstract: Rapid advancement in Artificial Intelligence (AI) has transformed the dynamics of interaction between organizations and consumers. The rapid emergence and adoption of AI chatbots have ushered in a new era of convenient and efficient customer service. This paper addresses the gap of how Gen Z perceives chatbots as an alternative for service interaction, considering that this sample of the population is relatively more tech savvy and understands technology better. Utilizing semi-structured interviews for in-depth interaction, a thematic analysis reveals six key themes: trust and reliability, nature of interaction, perceived usefulness/ease of use, advantages, disadvantages, and areas of improvement. Gen Z generally views chatbots as limited in handling complex queries, highlighting the importance of human intervention and database expansion. The identified themes provide valuable insights for organizations to highlight strengths and address weaknesses in AI chatbots' interactions with customers. The findings assist managers responsible for technology implementation in understanding customer pain points, fostering enhanced value for both users and organizations leveraging chatbots. This paper offers a comprehensive analysis of user experiences to illuminate the advantages and shortcomings of chatbots as service agents.

Keywords: Chatbot, Gen Z, customer perception, thematic analysis, India.

Introduction

The advent of digital technologies has ushered in a transformative era, reshaping not only the way businesses operate but also influencing the preferences and behaviour of the tech-savvy Generation Z consumers (Kwangsawad & Jattamart, 2022). A multitude of factors, such as emphasis on frictionless customer experiences, the emergence of digital natives, widespread

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access to smartphones and the Internet, prompt business response for competitive advantage, a focus on enhancing efficiency and minimizing costs, and the easy accessibility of digital technologies, have all contributed to the widespread adoption of these cutting-edge digital tools (Kala & Chaubey, 2023). As organizations strategically respond to these forces to gain a competitive edge, the integration of cutting-edge digital tools has become ubiquitous. In recent decades, a widespread growth has unfolded across various human interactive domains, propelled by technological advancements that facilitate the widespread adoption of information sharing and communication technologies by consumers and organizations (Xiang *et al.*, 2021). The modern human-technology interaction has paved ways for organizations to build interfaces, different from traditional models to assist customers in novel ways (Ul *et al.*, 2019). Modern technologies have forced organizations to make services and communication to be more convenient, ensure continuous availability, reduce access time for customers, and optimize resource management efficiency (Calvaresi *et al.*, 2023). Consequently, businesses are transforming their service encounters and experiences through automation (Mcleay *et al.*, 2021), with chatbots emerging as integral components (Adam *et al.*, 2021).

Chatbots are predominantly text-based conversational agents that simulate conversation with users (Ashfaq *et al.*, 2020). They evaluate user inputs and respond using artificial intelligence and natural language processing, enabling automated interactions in many web platforms and apps. Service interfaces are becoming technology-driven with chatbots (Larivière *et al.*, 2017). To improve productivity and reduce expenses, organisations are promoting chatbot functionalities on websites and mobile apps for 24/7 availability (Adam *et al.*, 2021; Gilbert *et al.*, 2004). AI-driven chatbots can engage clients at various service levels and perform routine and non-routine tasks. Customers' portfolios and historical records inform their personalised service recommendations and advanced counselling (Rust, 2021). AI technology is rapidly changing service encounters, with frontline staff receiving support or being replaced by these technologies (Castillo *et al.*, 2021). As organisations combine these advances, digital penetration in the service process is increasing, signalling a new age in service delivery.

The worldwide automation market grew from $186 billion in 2019 to $214.3 billion in 2021, demonstrating widespread adoption of automation technology (Statista, 2023). The AI market is expected to reach US$241.80 billion in 2023, with a 17.30% annual growth rate (CAGR 2023-2030) and a market volume of US$738.80 billion by 2030 (Statista, 2023); and $1,811.75 billion by 2030, according to Grand View Research (2023). IBM (2022) found that 57% of Indian firms used AI. Chatbots, adaptable and easy to use, bridge the gap between users and advanced AI systems. Many customer service and support professionals believe chatbots are the future. They believe that well-designed chatbots can improve customer experience and inspire good emotions at a cheaper cost than live conversations. As the globe moves towards

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automation, so does the service business, including how firms interact with clients. Chatbots are being used by customer service and support executives, but customers rarely use them, showing they are ineffective at helping customers achieve their goals. According to Gartner, only 8% of customers utilised a chatbot in their last customer care experience, and only 25% would use one again. Gartner expects chatbots to become the main customer care channel in five years (Gartner, 2023).

Most customers still use traditional methods to interact with firms' service representatives, and, while there are many studies and surveys showing industry's aggressive efforts to adopt and implement chatbots, the literature lacks practical reasons why customers do not accept them. Each Gen X, Y, and Z has unique traits that affect their technological adoption (Agarwal, 2019). Gen Z, digital natives, loves technology for visual, interactive, and real experiences, whereas Gen X and Gen Y utilise it for adaptability and social connectivity. Thus, Gen Z's digital fluency, preference for quick communication, tech-savviness, and openness to new digital trends make them ideal chatbot adopters (Alex & Lawrence, 2021). Considering this, we analyse Gen Z Indian customers' views on chatbots as service agents. India is an ideal place to investigate Gen Z's AI chatbot perception for various reasons. Gen Z is a substantial part of India's diversified population. Second, India is advancing technologically and Internet penetration is rising, especially among youth (Galdinus *et al.*, 2023). Studies of Gen Z in this tech-savvy milieu can reveal how technology affects their views on AI chatbots. Third, India has a vibrant start-up scene, and many companies are using AI chatbots. Gen Z's perception can reveal these technologies' real-world adoption and usability.

This study aims to achieve two key objectives: (a) to examine the perception of Gen Z towards chatbots for service interaction; and (b) identify the priority areas and concern areas related to chatbot interactions. The insights derived from this research will help organizations, decision-makers, chatbot developers, and managers responsible for the integration of artificial intelligence into customer services. By comprehending crucial aspects, thrust points, and potential areas for improvement, these stakeholders can enhance the development and integration of chatbots, ensuring more effective service delivery to the tech-savvy youth in India.

Literature Review and Theoretical Framework

Chatbot adoption

Chatbots are predominantly text-based conversational agents that simulate conversation with users (Ashfaq *et al.*, 2020). These are automated programs which are used to communicate with humans through text or chat exchange (Blut *et al.*, 2023; Ciechanowski & Przegalinska, 2017; Sivaramakrishnan *et al.*, 2007). Chatbots are used by organizations to interact with customers/potential customers in providing them service solutions. These chatbots can assist customers from anywhere (Chung *et al.*, 2018) and are capable of providing the same interpersonal experience to them as they would receive in an offline store (Sivaramakrishnan *et al.*, 2007). Thereby, chatbots not only provide required information to customers but also act as personal assistants to them (Mogaji *et al.*, 2021; Sivaramakrishnan *et al.*, 2007). These chatbots also act as virtual agents and companions, other than being an assistant. As virtual agents, they provide uninterrupted service and help in reduced response time which are seen as important factors to achieve customer satisfaction (Adam *et al.*, 2021).

As per Statista (2023), the size of the chatbot market is forecasted to reach around US$1.25 billion in 2025, which is a great increase from the market size in 2016 that stood at US$190.8 million. In the case of investment in marketing technology in the Indian market as of 2022, chatbots stand at a high 32%, along with data analytics and marketing automation (Statista, 2023). This means marketing professionals see chatbots as a way forward for future technological integration in the industry for efficient and cost saving processes. Chatbot usage has found significant growth and an upward trend across industries and geographic locations. These industries are segmented for the most part into Banking, Financial Services and Insurance; Healthcare; IT and Telecommunication; Retail; and Travel and Hospitality. The AI market share was over 40% in the IT industry (Statista, 2021) and has been making continuous in-roads in other industries as well.

Chatbot: user experience

Both practitioners and researchers have emphasized the potential advantage of using chatbots, including time-efficiency, reduced costs, and enhanced customer experience (Scherer *et al.*, 2015). These advantages serve as the foundation for more and more firms to adopt and integrate the chatbot system in their service department for improving customer interaction. The chatbots have been tested for perceived benefits and they are proven to be capable of interesting conversations with prompt responses at any time of the day (Wu *et al.*, 2020). Chatbots offer significant advantages to customers, including time-saving ability, quality information, and 24×7 availability (Ciechanowski & Przegalinska, 2017; Chung *et al.*, 2018). The accessibility provided by chatbots allows customers to engage with firms at any time, making it a crucial enabler for those who choose chatbot interactions. With minimizing the use of standard phrases, chatbots could achieve high conversational ability and will be more acceptable to the users (Rese & Tränkner, 2024). Chatbots have found their way into organizations' processes, especially service interaction, as they provide personalized virtual assistance, 24×7 availability and seamless customer experience (Kamoonpuri & Sengar, 2023;

Chung *et al.*, 2018; Eun *et al.*, 2010). Ashfaq *et al.* (2020) have found that engaging with a chatbot can be an enjoyable and delightful experience, leading to positive emotions that ultimately enhance user satisfaction. By assisting customers in various stages of their purchase journey (Hoyer *et al.*, 2020), the chatbot technology can transform their experience (Fan & Han, 2021) and make it a standout in the era of high competitiveness for an audience's attention.

On the other hand, despite these technological advancements, customers continue to have unsatisfactory encounters with chatbots, where unsuitable responses to their request results in a gap between their expectations and system performance (Adam *et al.*, 2021). The literature reveals how a low degree of openness to adoption of technology or being more favourable towards using traditional tools would result in negative outcomes for customers' adoption of chatbots and similar tech aids (Mcleay *et al.*, 2021). Findings of new identified dimensions suggest that technology adoption is directly related to perceived risk regarding customer's information and their knowledge adequacy in handling technology tools (Ganguli & Roy, 2011). Several limitations have been identified in the use of chatbots, including issues such as response time, privacy concerns regarding customer-shared information, and users' preference for human interaction over chatbots (Pillai & Sivathanu, 2020). Additional studies indicate that customer apprehensions about privacy and the perceived immaturity of technology contribute to reservations regarding chatbot usage frequency and intention (Luo *et al.*, 2019). Barriers to chatbot adoption and sustained interaction also encompass factors like perceived ease of use, perceived enjoyment, and reliability (Gilbert *et al.*, 2004).

Despite the increasing integration of chatbots as customer service representatives in recent years, significant challenges persist across all age groups. Issues such as the need for a sense of enjoyment or fun, and the trust to share crucial information with chatbots serve as major hurdles. Additionally, customers may feel discomfort when they realize they are not interacting with a human representative, believing that chatbots struggle to understand complex problems and may misinterpret them (Ashfaq *et al.*, 2020). Kwangsawad & Jattamart (2022) have also found that personal barriers, including technology anxiety, dissatisfaction with low-quality information from chatbots, and solutions that fail to meet customer expectations, impact the adoption of chatbots.

TAM-ISSM integrated model

This study utilized an integrated model that combines the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM) to examine users' perceptions of chatbot usage. TAM, a widely employed model, has been applied across diverse contexts to investigate technology adoption intentions (Meidute-Kavaliauskiene *et al.*, 2021; Zhou, 2013).

Additionally, it has been used for chatbot adoption in sectors such as banking (Nguyen *et al.*, 2021) and tourism & hospitality (Pillai & Sivathanu, 2020). Past research has identified perceived usefulness (the user's confidence in a technology's ability to efficiently assist in task completion) and perceived ease of use (the user's expectation of the system's effortlessness) as key drivers for technology adoption (Davis *et al.*, 1989; Venkatesh *et al.*, 2000; Isaac *et al.*, 2018; Ashfaq *et al.*, 2020; Nguyen *et al.*, 2021).

The Information Systems Success model, as proposed by Delone & Mclean (2003), emphasizes three quality aspects: information quality, system quality, and service quality. Information quality denotes the system's capability to deliver appropriate, timely, precise, and clear information. System quality highlights a user-friendly arrangement of the visible elements of technology. Service quality refers to how well users' needs are met by technology. In the context of evolving technological environments and changing consumer interaction patterns, Law *et al.* (2020) highlights the necessity of integrating various models to effectively study the phenomenon. Consequently, we integrated these models to formulate comprehensive themes for this study.

Research Methodology

This study attempts to examine the perception of Gen Z Indian consumers (born between 1995 and 2005) towards chatbots. Students were deemed the most appropriate prospective respondents for the study. To cater for diverse viewpoints, we attempted to include students of various educational programs in our sample. Undergraduate and postgraduate students of Business, Law and Engineering programs were contacted. The participants were randomly invited for the interaction with a pre-requisite that they must have interacted with chatbots before. Non-probability purposive sampling, where researchers select a sample based on respondents' knowledge about research, was used in the study. The researcher briefed the context of the study to the prospective respondents. The sample size turned out to be 40 for this study, which was finalized as data saturation began with repeated and similar responses to the questions asked. Interview questions were formed from significant work in the area (Eun *et al.*, 2010; Bolton, 2011; Pal & Singh, 2019; Ashfaq *et al.*, 2020; Pillai, 2020; Talwar *et al.*, 2020; Nguyen *et al.*, 2021).

Over the course of five weeks (between October-November 2022), face-to-face semi-structured interviews were conducted. Each interview lasted, on average, 20 minutes. Some interviews were audio-recorded with the consent of participants and later transcribed, whereas other interviews were limited to researcher notes. The language of interview was English. A transcript of 51 pages was prepared from the interviews and an additional 11 pages of researcher notes were made during the interviews to cross check the information shared by the respondents. To ensure validity and reliability, two researchers who attended the interview and discussion jotted down their notes independently. Later, they deliberated and combined the data, which was often done for several hours after the interviews or at the end of the day. Furthermore, these data were shared with the study participants to achieve construct validity.

To discover and analyse the perception of respondents, thematic analysis was employed. The method explored the explanations of the respondents and focused on how similar or different their insights were. Thematic analysis is a widely used technique for qualitative data sets created from inputs of research participants to investigate their perspectives and report the themes generated from them. It can ascertain reliable and insightful results with thorough analysis (Braun & Clarke, 2006). Thematic analysis helps to identify the prominent elements of a big set of data and sums them up, which is done by incorporating a structured methodology in processing of the data to arrive at a concise and systemized result (Kala, 2022). The statements were analysed to achieve the research objective by building categories and sub-categories. This was done manually without the use of any software. The thematic analysis with six phase steps, as suggested by (Braun & Clarke, 2006), was employed to identify insightful themes/categories correctly. Some statements presented in this paper were directly taken from the interview transcripts, while others were re-worded by referring to researcher notes. The keywords were identified from the transcripts of the interviews where frequent repetitions of the same topics were recognized and given a formal structure to develop the themes.

Findings

Table 1 presents participant demographics, indicating 60% female and 40% male respondents, all aged 18-24 (Gen Z cohort). Among them, 65% were undergraduates (BBA, BBA-LLB, B.Tech courses), spanning various study years, while 22.5% were postgraduates, and 12.5% were PhD candidates.

Table 1. Demographic Profile (n=40)

Demographics		Number	%
Gender	Male	16	40%
	Female	24	60%
Education Level	Undergraduate	26	65%
	Postgraduate	9	22.5%
	Doctorate	5	12.5%

Purpose of interaction with chatbots

As previous studies have shown that users prefer chatbots for information rather than transactional purposes (Hollebeek *et al.*, 2021; Malodia *et al.*, 2022), it was pertinent to examine the nature of chatbot interactions among Gen Z consumers. The findings indicate significant chatbot usage among Gen Z consumers, with 52.5% using them frequently and 42.5% occasionally. Information-seeking was the primary motivation, followed by providing feedback or registering complaints, aligning with findings in studies by Hollebeek *et al.* (2021) and Malodia *et al.* (2022), highlighting a preference for information-seeking over transactional purposes. The following are some of the responses from the respondents that built up the sub-categories:

> *R4: "I prefer seeking information from the chatbots only because I get to-the-point information." "I use it on a regular basis."*
>
> *R8: "I can actually search for data, and it will be presented mostly in clear, concise and quick manner."*
>
> *R17: "I don't really use chatbots unless like when I was going for my admissions, I went through the college sites and there were chatbots. So, when I had to reach to some person then I used the chatbots where they provided me with certain ID or some phone numbers."*
>
> *R31: "So the nature of interaction is like it is for information as well as for feedback and complaints. When it's not exactly complaints it is when I want to buy something."*

Table 2. Frequency of usage of chatbots and nature of interaction

Category	**Sub-category**	**Frequency**
Frequency of use	Rarely	2
	Occasionally	17
	Frequently	21
Nature of interaction	Information-seeking	31
	Feedback/Complaint	26
	Refund/Cancel	4
	Job-seeking	1
	Transactional	3

Perceived usefulness and perceived ease of use with chatbot interaction

Participants were asked to share their experiences and perceptions of chatbots based on their perceived usefulness and ease of use during interactions. The findings indicated that the reaction of respondents towards chatbot usefulness was mixed in nature. Database limitation was the major issue with chatbot usefulness. Similarly, factors such as being unable to address exact queries, limited set of Frequently Asked Questions (FAQs), technical issues during interaction, and redirecting the query to human assistance beyond a certain point were primarily impacting the ease of use of chatbots (Table 2). Conversely, respondents expressed that they see chatbots as valuable for obtaining quick responses, especially during odd hours when human representatives might not be available. Another notable benefit is the convenience of having all necessary information brought together by chatbots, eliminating the need to search the website independently. In these ways chatbots were labelled as useful or very useful. Some of the statements of the respondents are as follows:

> *R12: "I don't get what I am looking for, as chatbots do not have a lot of options. The problems that I face, it breaks down to one on one and those options are very less."*
>
> *R5: "It is useful when you don't have too much time to look for answers all over."*
>
> *R40: "For the problems they do not even understand, it gets escalated to like a chat manager or a process manager and then the whole thing is just managed by them."*
>
> *R17: "You cannot get fully satisfied with the answers because it's already fed in them and it's always, we contact you later for questions they cannot answer."*
>
> *R11: "Information database into that chatbot was very limited. So, like if I have a few questions, 5 to 6 questions, it would be like only 2 to 3 questions are installed in that database and so it could answer only those with those particular repetitive answers. Whenever the problems are outside of the FAQs, chatbots do not understand the questions."*
>
> *R1: "If you need any sort of unique solution about the whole thing, it just like waste your time for no reason."*
>
> *R33: "I found it (chatbot interaction) very confusing and irritating. They kind of redirected you to the website or to the customer care number."*

Table 3. Perceived usefulness and perceived ease of use

Category	Sub-category	Frequency
Perceived Usefulness	Very Useful	8
	Useful	15
	Not Useful	6
	Redirecting to human assistance	9
	Database limitation	23
	Remote assistance	2
Perceived Ease of Use	No difficulties	3
	Difficult/stressful	3
	Technical/system issues	14
	Unable to address exact query or limited set of FAQs	45
	Confusing	4
	Irritating	2

Trust and reliability in chatbot interaction

Next, participants were queried about the importance of trust in sharing information with chatbots and the reliability of the solutions they provide. Responses were mixed, with some perceiving chatbot solutions as unreliable, while others found them highly reliable, indicating

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a range of perspectives (Table 4). The table categorizes chatbots as either reliable or not, with explanations provided. Trust in the deploying organization's brand image emerged as a significant factor for those deeming chatbots reliable, reducing hesitancy in sharing information. Several respondents reported instances of chatbot representatives providing incorrect information, as highlighted in the following interview excerpts:

> *R34: "When you speak to a person of a company who is sitting in the customer department, they might provide you the old news but when it comes to chatbots, they are like legit updated."*
>
> *R12: "I don't get what I am looking for because chatbots do not have a lot of options. They have a basic minimal option."*

Respondents expressed reluctance to share personal/sensitive information with chatbots, citing discomfort. However, they mentioned that sharing general information was less concerning, considering the company already possessed many profile details. The analysis revealed that trust in chatbots correlated with the overall brand image and trustworthiness. The following selected interview statements highlight these sentiments:

> *R25: "It is the main thing, which is the reputation and the goodwill of the company. If there is no goodwill of the company, no one will give personal details to the company. So, as you mentioned, that trust is the key."*
>
> *R18: "When a company is introducing it (chatbot), it can be trusted because it already has access to all my data."*
>
> *R31: "Not completely (trusting the chatbot), just till the period that I feel if any information is more of a general thing, so no harm will be there."*

Table 4. Trust and Reliability of chatbot interactions

Category	Sub-category	Frequency
Trust & Reliability	Very reliable	14
	Reliable up to a certain extent	5
	Not reliable	17
	Incorrect information	8
	Trust chatbot due to image of the organization	11
	Prefer not sharing personal information	11
	They already have most information	2
	Comfortable in sharing non-sensitive information	5
	Trustfulness important since personal information is shared	7

Timeliness and empathy with chatbot interaction

Table 5 displays participant responses regarding the timeliness of chatbot solutions. The analysis revealed that delayed responses with uncertainties about response times is a prevalent concern. Despite this, some respondents did report receiving prompt or instantaneous replies to their queries. The following statements are excerpts from the interview transcripts:

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R4: "Yes, I get timely responses since they are very impromptu, and you can even talk to them at like 12 in the night and even then, you will receive a reply."

R9: "Sometimes when I wanted some information, it was very fast, the solution. But other times they were delayed."

Table 5. Timeliness and role of empathy with chatbots

Category	Sub-category	Frequency
Timeliness	Timely	11
	Instant/Immediate	7
	Late solution	18
	Uncertain	5
Empathy	Unable to understand urgency	3
	Unable to understand human emotion	4
	Lack of empathy does not affect.	14
	Lack of empathy lead to discomfort	2
	Lack of empathy affects	7

In Table 5, responses regarding the empathy aspect of chatbots are presented. Participants who elaborated further indicated that the chatbots' failure to grasp the urgency of their inquiries or the associated human emotions had a negative impact on their interactions. Conversely, those who asserted that the lack of empathy did not affect their conversations with chatbots argued that expecting empathy from a machine is unreasonable. Selected statements from the interview transcripts are provided below:

R2: "I expect professionalism in these things. More than empathy, I feel that the bots have to just provide more options."

R12: "I don't expect empathy from customer care (chatbot) where I am only finding information."

R14: "Yes it affects definitely because it doesn't understand what we actually are right now."

R37: "They cannot understand your human emotions, the urgency of your query and all those things."

Advantages and disadvantages in chatbot interaction

Table 6 presents insights from interviews on the advantages and disadvantages of chatbots. Noteworthy benefits include prompt responses and 24×7 availability for inquiries. Users highly value the ability to interact with chatbots, especially during unconventional hours when human support is unavailable. Conversely, a collective concern among participants revolves around the perceived lack of empathy in chatbots. While users acknowledge not expecting empathy from machines, they find its absence impacting interactions, particularly in conveying urgency or emotions. Additionally, respondents highlighted chatbots' limitations in handling complex issues, attributing this to their inability to comprehend queries beyond their stored database. The following are some of the excerpts from the interviews that capture these

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sentiments:

> *R19: "You get information instantly and you also get suggestions related to your questions if I am asking a certain question."*
>
> *R32: "one of the major advantages is that you get the solution instantaneously, you do not have to wait for the person to type it out because it is already there."*
>
> *R12: "if I have basic issues with any sites, I need an instant solution about anything I can always use the chatbots."*
>
> *R37: "If you do not have anybody around in order to help you out with the stuff, I think it is quite helpful for you because you don't have any information about how to handle that portal or something like that and then suddenly, they guide you much better."*
>
> *R30: "we do not get particular solution that we are asking for."*
>
> *R19: "It becomes offline from time to time, and it doesn't give me the answers that I'm looking."*
>
> *R25: "Sometimes they're not able to provide what actually you try to ask them."*
>
> *R15: "They cannot understand your human emotions, the urgency of your query."*

Table 6. Advantages & Disadvantages in chatbot interaction

Category	Sub-category	Frequency
Advantage	Quick response and Problem solved	25
	Suggestion prompts	5
	24×7 availability	17
	Easy to contact the firm	2
	Problem categorized already available	3
Disadvantage	Information confidentiality	3
	Technical non-feasibility of solutions	2
	Solution not provided	8
	Complex problems not solved	9
	Lack of personalized solution	3
	System issue/connectivity	5
	Incorrect problem interpretation	5
	Lack of empathy	21

Areas of improvement in chatbot interaction

In the concluding section of the survey, participants discussed the 'area of improvement', providing suggestions for enhancing future interactions with chatbots. Expanding the chatbot's query database to prevent frustration caused by limitations on question range is the most frequently mentioned recommendation. Many respondents proposed that human intervention could enhance the overall interaction experience, leading to smoother and timelier query resolution. Other notable suggestions encompassed improving query interpretation, incorporating voice commands, enhancing system quality, and ensuring

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information confidentiality. The following are a few of the statements from the interviews of the respondents:

> *R7: "So when chatbot doesn't really understand the query, then human intervention should be there."*
>
> *R36: "For the complaints I give, they can increase their database on this type of question."*
>
> *R2: "When we ask the question, we are not given the options of additional question so that would make the thing easier."*
>
> *R24: "Improving the first thing would be a database, extended database of set of questions, the solutions the bot could provide to the users."*
>
> *R10: "The chatbot interaction just lasts for 20 to 30 seconds whenever chatbot interaction is exceeding that there should be a person who looks into the chat correct from their side."*

Table 7. Areas of improvement in chatbot interaction

Category	**Sub-category**	**Frequency**
Areas of improvement	System improvement	5
	Addition of more queries/solution in database	16
	Human intervention	14
	Include voice commands	5
	Problem interpretation	10
	Information Confidentiality	6
	Addition of emotions	10
	Keyword search like option	3
	Make chatbot options easy to locate on webpage	2
	Personalized greeting	2

Figure 1 synthesises the findings of this study, creating six broad themes to highlight major factors affecting and guiding Gen Z users' perceptions of chatbot interaction. This representation provides a clear and tangible insight into the research findings, with subsequent sections of this article delving into each theme based on the responses of the interviewed participants.

Discussion and Implications

This study aimed to examine Indian Gen Z users' perceptions of chatbots and identify priority and concern areas in their interactions. Utilizing TAM and ISSM, the study found that Gen Z highly values the 24×7 availability of chatbots, aligning with literature emphasizing continuous availability and cost-saving as key reasons for chatbot integration (Schuetzler *et al.*, 2021; Nguyen *et al.*, 2021; Pillai & Sivathanu, 2020). Contrary to the perception of Gen Z as tech-savvy, this analysis reveals challenges in perceived usefulness, such as the chatbot's inability to interpret queries, technical issues, and database limitations (Trivedi, 2019; Eze *et al.*, 2021).

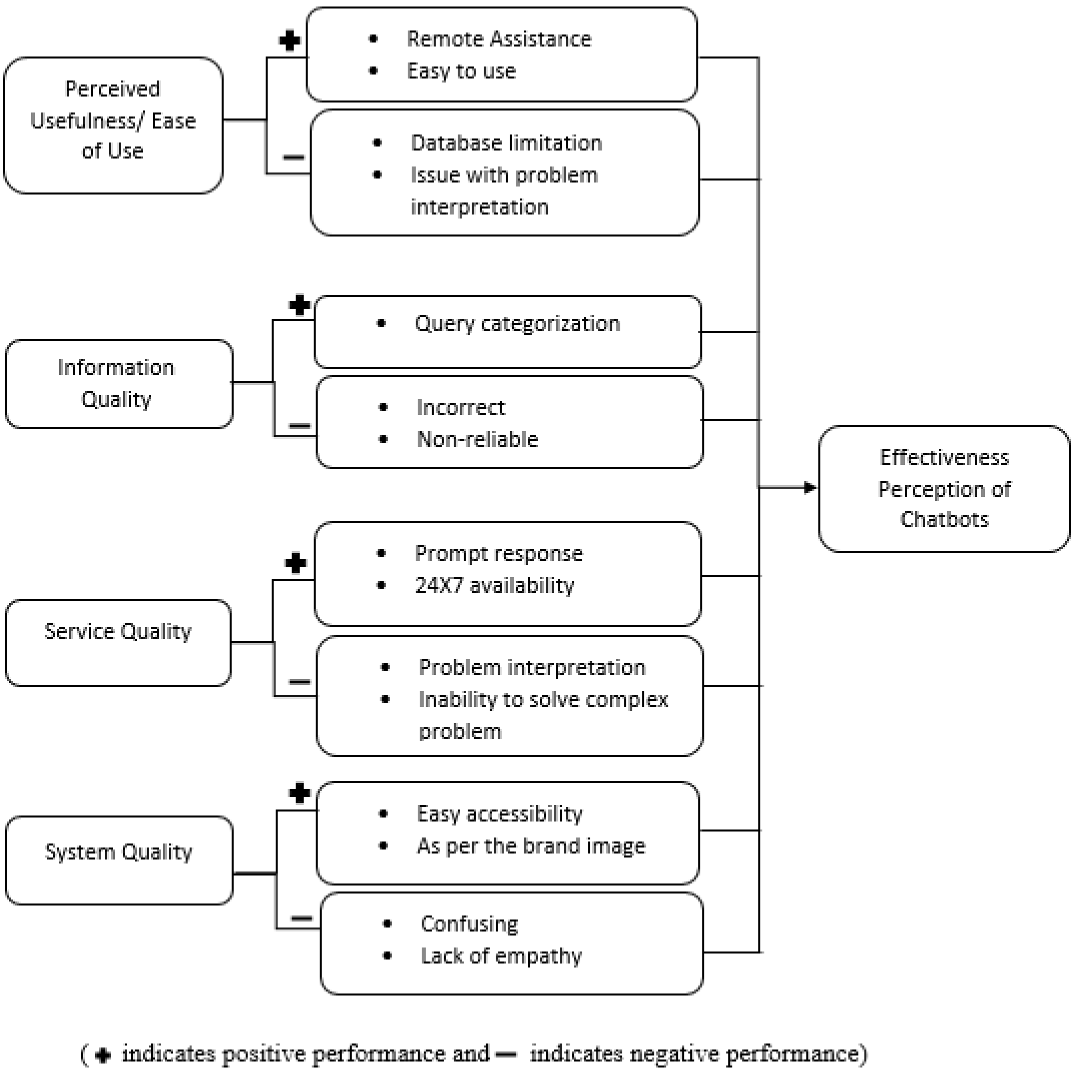

Figure 1. Summary of the findings for Effective Perception of Chatbots

While previous studies suggested Gen Z is less concerned about empathy in technology use, the findings indicate a significant concern regarding the lack of empathy in chatbot interactions (Kolnhofer-Derecskei *et al.*, 2017). Trust in chatbots among Gen Z is closely tied to the brand image of the organization. Users hesitate to share sensitive information, trusting the chatbot only as much as they trust the brand. The study underscores that assessing and improving chatbots should consider their reliability and trustworthiness, linked to the goodwill of the firm.

Additionally, the study emphasizes the importance of a robust knowledge base for successful service solutions. Gen Z respondents highlight the limitation of the chatbot's database as a major disadvantage, calling for an expansion to address a broader range of questions. The majority of interactions involve information-seeking or registering complaints/feedback, aligning with studies on the nature of communication channels influencing customer decisions (Polo & Sese, 2016). While some studies have indicated significant positive effects of both perceived usefulness of a chatbot and trust on both attitude towards chatbots and satisfaction (Soares *et al.*, 2018), it would have been better tested if participants' motive was to do more of purchase actions rather than just query-based interactions.

This study has both theoretical and managerial implications, seeking a deeper understanding of Gen Z users' perceptions of chatbots as service agents. For researchers and academics, the qualitative study provides rich information from firsthand experiences (Braun & Clarke, 2006), offering new variables like empathy for exploring user satisfaction and continuance intention. This aligns with recent literature highlighting the negative impact of empathy on customer satisfaction (Bock *et al.*, 2016; Li & Zhang, 2023). This study also contributes to theory by integrating factors from TAM and ISSM, aligning with the call for integrating models in the evolving technological environment and changing consumer interaction patterns (Law *et al.*, 2020).

For managerial implications, the findings suggest the need to train chatbots for diverse interaction styles, addressing a wide array of query-based conversations, from transactional to unique, one-off problems. This would enhance the chatbot's ability to interpret a broader range of questions effectively. As inferred from the interviews, users express annoyance when chatbots redirect them to FAQs, emphasizing the importance of providing solutions during the interaction to foster a positive perception. User dissatisfaction often stems from receiving incorrect information, a concern echoed in this study and supported by recent findings (Rese & Tränkner, 2024). To enhance user experience, chatbots, being fundamental text-based informative AI tools, should explore audio-based alternatives, expanding the user base. As noted in a recent study (Kamoonpuri & Sengar, 2023), voice notes from users offer valuable insights, such as voice intonation, mood, and energy level, potentially useful for marketing strategies.

Finally, as chatbots progressively replace human customer service representatives, it is recommended to instil them with traits resembling their human counterparts. Whether driven by anthropomorphism, as suggested by studies (Moussawi *et al.*, 2021; Gursoy *et al.*, 2019), or traits like empathy revealed through user interviews, managers should prioritize creating a more humane service interaction environment (Kala, 2022). This study contributes to the existing chatbot literature by systematically recording, analyzing, and presenting the advantages and disadvantages arising from user interactions, offering categorical areas for improvement. These insights can guide academicians, researchers, and managers in developing more robust chatbot systems with refined processes and constructs for measurement and enhancement of user satisfaction and continued usage.

Conclusion

Technology innovation and implementation have been fast paced across all industries, and so has their adoption. Organizations are focused on improving both products and the efficiency of resources that help achieve these advancements. To attain this feat, organizations set their eyes on cost-saving and improving service quality. As a result, chatbots are actively being integrated into their systems in the hope of achieving automated functionality that is prompt, robust, available, and efficient. This study puts forward key advantages of chatbot interaction, such as easy accessibility, prompt responses, and 24x7 availability, while also highlighting shortcomings like problem interpretation, inability to solve complex problems, and database limitations. The qualitative analysis helped identify major areas for improvement, including expanding the chatbot database, human intervention, and improved problem interpretation by the chatbot. These factors could enhance customer experience and contribute to building a competitive advantage. This becomes essential, as major reports (Statista, 2022; McKinsey, 2023) and studies (Chi *et al.*, 2020; Mcleay *et al.*, 2021) predict immense contributions and breakthroughs in AI in the coming years. This study aims to address a significant aspect from the young customers' point of view by presenting their perceptions about chatbot features.

Limitations and Future Direction

The limitations of the study suggest avenues for future research. First, considering the focus on Indian students, generalizing results requires caution; larger samples in future studies can enhance generalizability. While this study employed a qualitative approach, future research could benefit from incorporating quantitative and mixed methods for a more precise understanding of user perception. In this study, researchers have taken "chatbot" as a generic term. Exploring different types of chatbots and industry-specific adoption variations in comparative studies would offer valuable insights.

Additionally, this study focuses on a country like India which has strengthened its technological prowess and automation integration to a considerable level. Comparative research across countries, including developed, emerging, and developing nations, would contribute to understanding the impact of technological advancements. As chatbot usage has become substantial in certain industries, assessing user satisfaction and continuance intention becomes crucial for developers, marketers, and organizations to enhance user experience and address challenges.

Lastly, future studies should evaluate the anthropomorphism aspect in chatbot adoption concerning both adoption and satisfaction contexts.

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Impact of Technology-Enabled Personalization on the Adoption of Mobile Banking

An Experimental Study

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Abstract: New technologies such as artificial intelligence and Big Data offer an opportunity in terms of personalization of products and services, particularly in mobile banking services. Previous researches have provided mixed results regarding the causal or moderator role of personalization in the adoption of mobile services. This research aims to provide a response to this discordance by using an experimental method in the context of mobile banking services. Results regarding the impact of technology-enabled personalization along with age on the adoption of mobile banking services confirm the causal impact of technology-enabled personalization on facilitating conditions (FC), hedonic motivation (HM), perceived confidentiality (PC), and the intention to use mobile banking. Findings and discussions across age and gender groups could guide future empirical research in this area.

Keywords: M-Banking, Experiment, UTAUT, Technology-enabled Personalization, perceived privacy

Introduction

With a large customer base, banks can benefit from new marketing and communication tools, which offer the possibility of mass customization while offering innovative products. This is a major challenge because many organizations today are saturated with mass automation and homogenized products and services (Martins *et al.*, 2014).

The growth of the smartphone market has encouraged the banking sector to create innovative digital applications that provide customers with the convenience of carrying out transactions. These are mobile banking services (Saparudin *et al.*, 2020).

Motiwalla et al. (2019) admit that emerging technologies allow personalization of system functionality based on contextual variables derived from the experiences and demographics of each user group, such as gender, age, education and income information.

According to Dauda & Lee (2015), technology acceptances are theories that focus on factors that influence the decision of accepting and using a specific technology. In this context, the most studied models in the literature on technology acceptance are the technology acceptance model (TAM) (Davis, 1989); the theory of planned behaviour (TPB) (Ajzen, 1991), which is developed from the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975); and a hybrid model combining the constructs of TAM and TPB (Taylor & Todd, 1995). Additionally, the following theories were largely adopted in the field of technology acceptance: the theory of diffusion of innovation (Rogers, 1983); the social cognitive theory (Bandura, 1986); the PC use model (Thompson *et al.*, 1991); the motivational model (Davis *et al.*, 1992); and the Unified Theory of Acceptance and Use of Technology (UTAUT) that was published under two versions UTAUT1 and UTAUT2 (Venkatesh *et al.*, 2003; Venkatesh *et al.*, 2012).

In terms of the mobile application literature, little attention has been paid to the role that personalization plays in technology acceptance (Cheng *et al.*, 2020). In the banking sector, we have noticed that studies generally focus on online banking services (Salem *et al.*, 2019; Wang *et al.*, 2017). Regarding M-banking, previous research has focused on studying customer satisfaction (Albashrawi & Motiwalla, 2015; Altobishi *et al.*, 2018). The relationship between personalization and the UTAUT 1 and 2 theories (Venkatesh *et al.*, 2003; 2012) has been discussed in different contexts, such as mobile news applications (Cheng *et al.*, 2020), e-government services (Krishnaraju *et al.*, 2016), and online banking (Wang *et al.*, 2017). Thus, this study is motivated by the lack of literature on the role of personalization in M-banking services.

After an in-depth review of the literature on the role of personalization in the adoption of mobile services in several contexts, and the examination of the factors which influence the adoption of these services in the banking sector, it appears that results of previous research are not unanimous regarding the moderating impact (Albashrawi & Motiwalla, 2015; Cheng *et al.*, 2020) or causal impact on the adoption of mobile banking services (Saeed, 2011; Asif & Krogstie, 2013; Altobishi *et al.*, 2018; Zalloum *et al.*, 2019). Hence, the relevance of using experiment, which proves to be an adequate method for analysing the role of personalization (Lee *et al.*, 2012; Krishnaraju *et al.*, 2013; Wessel & Thies, 2015).

This study conducted firstly an experiment to confirm the role of personalization in the adoption of mobile banking services at the level of the UTAUT relationship, perceived confidentiality and the intention of adopting mobile banking services. Secondly, based on the experiment results, relationships of the research model are assessed using a Structural Equation Modelling (SEM) analysis.

Literature Review

Technology-enabled personalization (TEP) is defined as the integration of physical and digital personalization dimensions at the point of sale to provide individual customers with relevant, context-specific information, based on combined historical and real-time data (Riegger *et al.*, 2021).

According to Albashrawi & Motiwalla (2015), personalization involves personalizing the user interface and graphics according to the needs of each user. Personalized mobile banking applications require the use of customer profiles, customer preferences, prior mobile banking usage data and social media data.

Technology-enabled personalization (TEP) has become possible in the context of M-Banking thanks to the following technologies: artificial intelligence, machine learning, recommendation systems, the Internet of Things, and Blockchain. TEP encompasses two dimensions: the physical dimensions of M-Banking personalization services, such as locations, facial expressions and real-time interactions (video banking); and the digital dimensions of personalization, which concern banking data, social networks, e-commerce, and websites (Khemiri & Jallouli, 2022).

Previous researches argue that the UTAUT was widely used to study individual usage behaviour of various information systems. The UTAUT demonstrates good generalization and high explanatory power in computer system research, and it has rarely been combined with a data mining tool that can improve its validity in the context of mobile banking (Albashrawi *et al.*, 2017). According to Venkatesh et al. (2012), UTAUT2, which is an evolved form of the UTAUT (Venkatesh *et al.*, 2003), is composed of performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), social influence (SI), hedonic motivation (HM), price value (PV), and habit (HT).

In addition, Venkatesh *et al.* (2012) show that different cohorts of consumers attach different weights to various factors that influence their technology use, which can potentially be attributed to differential learning abilities and social roles by age, experience, and gender.

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Results of previous studies are not unanimous regarding the role of age and gender in accepting Internet and mobile services. Indeed, according to Laukkanen (2016), age and gender appeared to be significant variables in the acceptance of mobile banking services. On the other side, for non-adopters of mobile banking, the rejection decision is explained by gender, while age explains the rejection of Internet banking. Additionally, results show that women appear more likely to reject mobile banking than men. Furthermore, the study by Faqih et al. (2015) shows that the gender dimensions has no influence on the adoption of m-commerce technology.

After careful consideration of previous publications regarding the nature of the impact of personalisation, gender and age on mobile banking adoption factors and intention to use M-banking, this research provides the theoretical foundation of the set of hypotheses related to the UTAUT2 theory and perceived confidentiality in the M-banking context, subject to the experimental protocol that will be adopted in a second step.

According to Islam (2017), personalization has a positive impact on behavioural intention in the case of mobile Internet. Indeed, personalization was found to be an important factor alongside the existing factors of the UTAUT model. Moreover, Salem et al. (2019) admitted that customer value for online personalization has a causal impact on the use of online banking services. Thus, the preceding developments support the following hypothesis:

H1: Personalization based on new technologies has a positive impact on the intention to use M-Banking services.

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003, p. 447). According to Wang et al. (2017), personalization has a significant impact on the performance expectations and responses of customers who are either inexperienced with e-banking in general or familiar with a completely different system. This shows that personalization leads them to find more utility in their experience. Additionally, personalization helps reduce the time required to complete tasks, improve efficiency, and deliver the desired information in the right form to targeted users (Cheng *et al.*, 2020). Moreover, Fernandez-Lanvin et al. (2018) found that there is consistency in the execution times of individuals across different tasks on e-commerce websites, and that age and gender are sufficiently determining factors to allow for personalized automatic profiling. According to Yapp et al. (2018), personalization is important for female users, because it could contribute to enhance their performance expectations. Results show that women express their need to have services capable of solving their problem related to machine interaction and doing more work in a short time.

http://doi.org/10.18080/jtde.v12n1.891

Thus, in this research the following hypotheses are stated:

H2-1: Personalization based on new technologies has a positive impact on performance expectancy.

H2-2: The impact of personalization based on new technologies on performance expectancy is moderated by age.

H2-3: The impact of personalization based on new technologies on performance expectancy is moderated by gender.

Regarding the third variable, Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh *et al.*, 2003). The results of Cheng et al. (2020) show that personalization does not have a moderating impact on the relationship between effort expectancy and continued use intention of mobile news applications. Moreover, according to Wang et al. (2017), personalization will have an impact on the expected effort for online banking services. Indeed, customers indicate that personalization leads them to find more utility in their experience and improve their perceived ease of use of e-banking. Kumar et al. (2004) suggest that, at the level of users' perception of a personalized interface, personal characteristics such as age and gender have an effect on the perception of the ease of use of web pages. The following hypotheses are stated:

H3-1: Personalization based on new technologies has a positive impact on effort expectancy.

H3-2: The impact of personalization based on new technologies on effort expectancy is moderated by age.

H3-3: The impact of personalization based on new technologies on effort expectancy is moderated by gender.

The variable "facilitating conditions" is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system" (Venkatesh *et al.*, 2003). Furthermore, Cheng et al. (2020) admit that through personalized news applications users must feel like they are getting a special service. In this sense, facilitating conditions refer to quality services, such as the timely delivery of updates, push notifications, or breaking news to users on their favourite topics, instantly and without any technical malfunction.

According to Krishnaraju et al. (2016), the moderation effect of Web Personalization on facilitating conditions was not significant. On the other hand, Siyal et al. (2024) admit that personalization has a significant and positive effect on facilitating conditions for mobile commerce applications. Additionally, Wijaya & Sari (2021) prove that the relationship between Customer Relationship Management (CRM) chatbots and user preferences is influenced by demographic variables including age and gender. This study discussed the attributes involved in human chatbot interaction considered as facilitating conditions of using CRM systems.

Based on these developments, the following hypotheses are stated:

H4-1: Personalization based on new technologies has a positive impact on facilitating conditions.

H4-2: The impact of personalization based on new technologies on facilitating conditions is moderated by age.

H4-3: The impact of personalization based on new technologies on facilitating conditions is moderated by gender.

As for "social influence", this variable is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh *et al.*, 2003). As for the role of personalization, according to Cheng et al. (2020), personalization does not have a moderating impact on the relationship between social influence and continued use intention of mobile news applications. On the other hand, the study by Blom & Monk (2003) showed that personalization was incorporated by many of the participants' friends and it was a major cause of adoption. Oyibo et al. (2017) found that, in general, men and women, as well as younger and older people, differ in their susceptibility to social influence strategies in persuasive technology. In fact, men and younger people are more susceptible to the respective persuasive strategies than women and older people.

H5-1: Personalization based on new technologies has a positive impact on social influence.

H5-2: The impact of personalization based on new technologies on social influence is moderated by age.

H5-3: The impact of personalization based on new technologies on social influence is moderated by gender.

Regarding hedonic motivation, this variable is defined as "the fun or pleasure derived from using technology, and it has been shown to play an important role in determining technology acceptance and use" (Venkatesh *et al.*, 2012). As for personalization, according to Haq & Ghouri (2018) personalization does not influence consumer behaviour towards adoption through emotional value. On the other hand, Krishnaraju et al. (2016) admit that, with a higher level of web personalization based on a recommendation system, hedonic motivation will have a stronger impact on the intention to use E-government. Additionally, Sung et al. (2009) suggested that personalization helps technology users feel increased attachment to a product, which can help accelerate emotional engagement. Furthermore, the research by

Abdullahi et al. (2019) on the personalization of persuasive health interventions found that women and older adults (over 65 years old) are more strongly associated with emotional well-being to promote subjective well-being. Based on these results, the following hypotheses regarding hedonic motivation are stated:

H6-1: Personalization based on new technologies has a positive effect on hedonic motivation.

H6-2: The impact of personalization based on new technologies on hedonic motivation is moderated by age.

H6-3: The impact of personalization based on new technologies on hedonic motivation is moderated by gender.

Price value is defined as "consumers' trade-off between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh *et al.*, 2012). According to Tyrväinen et al. (2020), personalization has reduced customer search and cost evaluation, which has increased their loyalty. Rust (2020) acknowledged that the low cost of personalization in the information services environment makes personalization more feasible. Moreover, Bloom (2003) admits that it is easy to understand that the cost of personalizing can affect a user's disposition to personalize, especially for users in younger age groups. In addition, Lastner et al. (2019) admit that personalized dynamic pricing is influenced by gender. Indeed, their study reveals a significant interaction between gender and reference price.

Based on these developments, the following hypotheses are stated:

H7-1: Personalization based on new technologies has a positive impact on price value.

H7-2: The impact of personalization based on new technologies on price value is moderated by age.

H7-3: The impact of personalization based on new technologies on price value is moderated by gender.

Habit is defined as "the extent to which people tend to perform behaviours automatically" (Venkatesh *et al.*, 2012). Krishnaraju et al. (2016) confirm that website personalization has no moderating effect on the relationship between habit and behavioural intention. However, Cheng et al. (2020) admit that the benefits of both utility and personalization features contribute to strengthening the effect of habit on the use of new apps, especially when users are satisfied with their experiences of obtaining preferred content. Hutto et al. (2015) argue that the multitude of details provided by users about their personal usage habits of social media technologies, their sharing behaviours, their communication practices, their preferences, their problems, and their concerns constitute a rich source of relevant information for personalization. Indeed, older women, who have greater technological confidence and more positive attitudes towards ICT, tend to access social media from their home personal computer and generally want to stay connected with their family. Therefore, we state the following hypotheses:

H8-1: Personalization based on new technologies has a positive impact on habit.

H8-2: The impact of personalization based on new technologies on habit is moderated by age.

H8-3: The impact of personalization based on new technologies on habit is moderated by gender.

According to Westin (1967), information privacy is defined as "the individual's ability to control when, how, and to what extent his or her personal information is acquired and used". Oliveira et al. (2014) admit that mobile banking is a highly personalized and highly sensitive service, and users are mainly concerned about privacy and security. Therefore, policymakers and financial institutions should focus on establishing a trusting relationship with the customer from the beginning.

Saeed & Bekhet (2018) show that personalization is an insignificant predictor of the intention to use mobile marketing. On the other hand, Hmoud & Varallyai (2020) acknowledge that, despite the fact that AI-based business information systems are in their early stages of diffusion, respondents have shown marginal trust despite not having used them yet. Furthermore, Guo et al. (2016) indicate that the effects of personalization on trust to use are stronger among young people. In addition, Sheehan (1999) proves that women are more concerned about their privacy than men in several types of online information gathering situations. In this research, we state the following hypotheses:

H9-1: Personalization based on new technologies has a positive impact on perceived confidentiality.

H9-2: The impact of personalization based on new technologies on perceived confidentiality is moderated by age.

H9-3: The impact of personalization based on new technologies on perceived confidentiality is moderated by gender.

Figure 1 provides an overview of the theoretical framework that summarizes the hypotheses proposed in this section.

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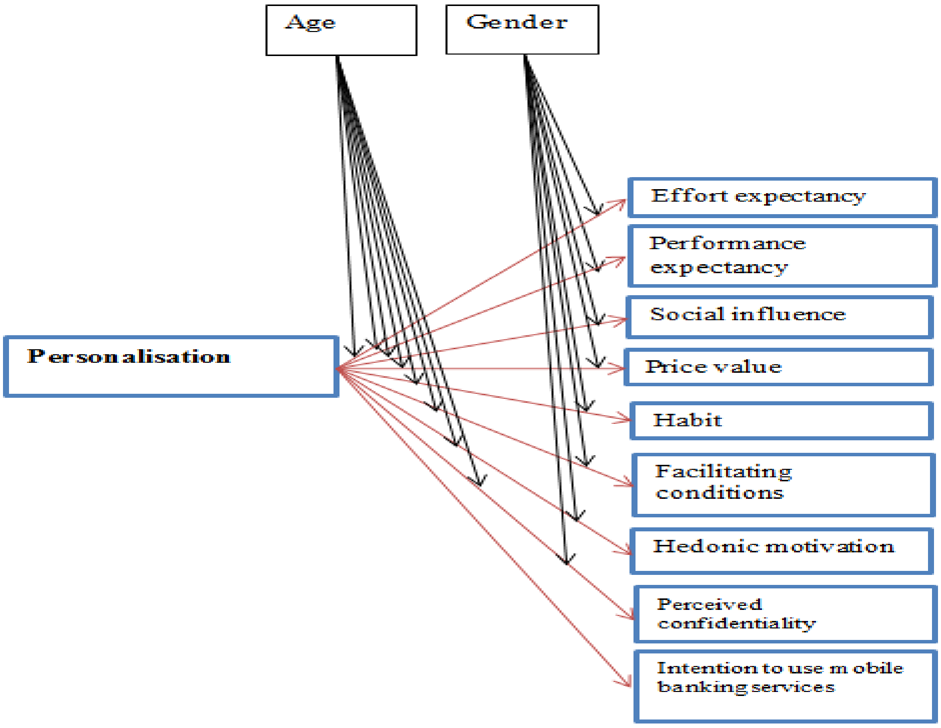

Figure 1. Conceptual framework of the impact of personalization on adoption factors and intention to use mobile banking services

Experimental Study

An experiment was conducted to study the effect of technology-based personalization on the adoption factors and adoption intention of mobile banking services. The explanatory variable is personalization. Thus, the dependent variables are performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, social influence, perceived confidentiality, price value, habit, and intention to use mobile banking services.

Design of the research experiment

A statistical experimental plan is designed following a factorial design of 12 cells (2x2x3), namely:

- 2 types of questionnaires — “A” (personalized application) and “B” (non-personalized application);
- 2 types of gender — “man and woman”;
- 3 age groups — “under 30 years”, “between 30 and 50 years”, and “over 50 years”.

A total of 986 participants were randomly assigned to one of the groups, in which questionnaire “A” was manipulated via an experimental design and questionnaire “B” was presented to a control group.

After explaining the design of the study and before carrying out the experiment, we have first checked the internal and external validity.

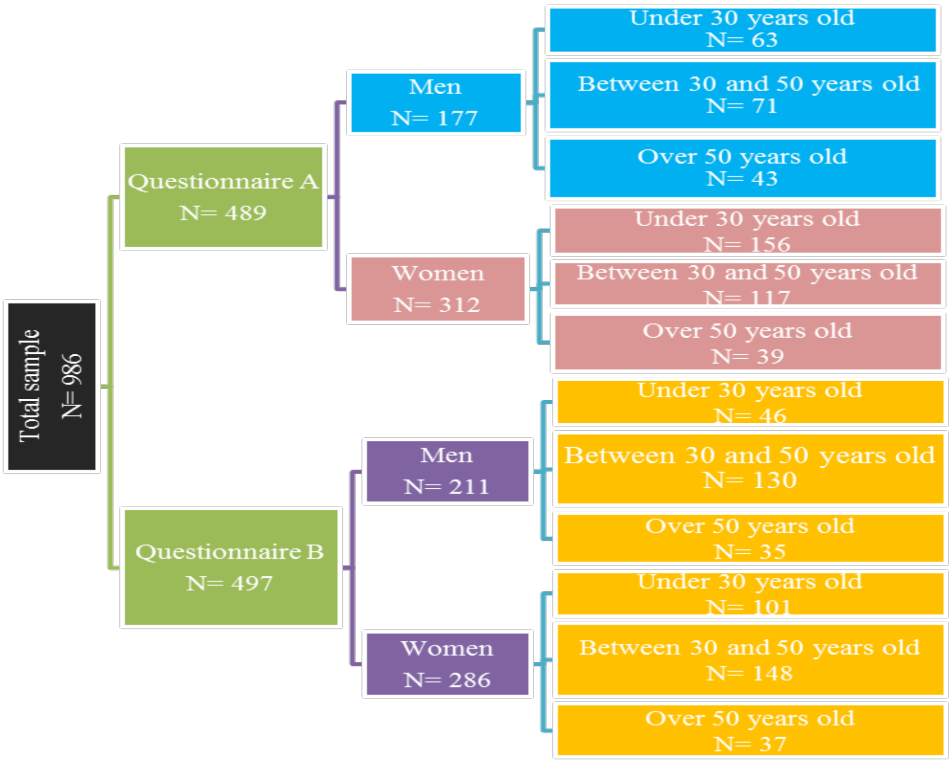

Figure 2. Sample structure

Concerning the history effect, we ensured that no events external to the experiment occurred at the same time and which could affect the dependent variable. In addition, to avoid the testing effect, two samples from the same population and with the same characteristics were used; one for testing and the other for experiment. Also, to minimize the selection effect, we proceeded to a random assignment of subjects to groups (A and B).

To reduce the effect of the instrument, we systematically tested the questionnaires with subjects representing the target population in order to obtain their qualitative feedback in terms of understanding, difficulty of response and duration of administration.

The experiment was carried out according to the following steps:

Step 0: *Introduction of the questionnaire*

The participant was informed that the questionnaire was part of scientific research in marketing.

First step: *Participant/client identification*

To simulate the customer's banking identity, the participant was asked to fill out an identification sheet concerning nationality, profession, gender and age.

Second step: *Classification of participants*

The respondent (test unit) is automatically assigned without their knowledge to the cells which correspond to their age and gender class (Figure 1). This action is done by the "Google form" algorithm while trying to follow the same processing that is done by artificial intelligence tools on mobile banking applications. Indeed, this processing has become possible thanks to access to vast volumes of customer and transaction data, across digital data, text, voice, image and facial expression (Davenport *et al.*, 2020).

Third step: *Description and knowledge test*

A description was introduced to explain the concept of mobile banking services to respondents: "*Banks provide their customers with applications that can be downloaded to mobile phones. It allows, among other things, to consult the balance, download account movements, order the bank card and check [cheque] books, etc. These applications are also called 'mobile banking applications'.*"

We first asked a question to test the frequency of use of the mobile application by the respondent to manage the bank account(s). We then asked the respondents to answer questions regarding the personalization variable before the experiment to avoid any kind of influence on his/her answers.

Fourth step: *Simulation of the bank card offer*

A Mobile Banking Application was chosen as the context for the experiment. We designed an image to simulate a real application (Appendix 1).

The simulation consists of displaying a poster containing a screenshot of a banking application installed on a smartphone, containing a set of services and a personalized bank card offer. Indeed, algorithm-based personalization allows applications to suggest the most appropriate content to users (Cheng *et al.*, 2020).

- The choice of services presented in the application was based on a search for mobile banking services on Google Store.
- The personalization of the card offer was manipulated by inserting two information attributes on wallpaper (the colour and the text message).

For men, we assigned the colour "blue". Cerrato (2012) suggests that blue is a masculine colour; it is very well accepted among men. For women, we used the "pink" colour. Psychologically, it is used to symbolize many characteristics, including femininity (Singh & Srivastava, 2011; Cerrato, 2012; Mohebbi, 2014). Concerning the control group, we chose the "gold" colour. Around the world, the "gold" colour is widely used by banks for cards that are offered to men and women without distinction. This colour, therefore, does not refer to any information or gender preference, based on the psychological and also contextual perspective (current practices).

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For age, we inserted personalized text messages for each age group. For example, for Men under 30, the message was: “Discover our new offer for men under 30”.

Concerning the control group, a standard message was set for all cells: “Discover our new offer”.

Fifth step: *Measuring Perceived Personalization*

The objective of this step was to measure or evaluate the effect of perceived personalization after the experience. A question was assigned to the respondent: To what extent does this message above seem personalized to you (adapted to your profile: age and gender)?

Sixth step: *Measure Questions*

The participant answered the remainder of the questions regarding the dependent and independent variables based on the same measures. The questionnaire was pre-tested by face-to-face interviews and on a sample of 16 online respondents in order to ensure proper understanding of the questions. At this stage of the research, it is indeed essential to ensure that the manipulation of the different stimuli is correctly perceived by the respondents.

Therefore, it was appropriate to verify that respondents perceived a high degree of personalization (vs low) when they were faced with a personalized application (vs non-personalized)

The statistical test used to verify the hypotheses is the analysis of variance (ANOVA), which allows one to verify if there are statistically significant differences between the groups. Indeed, the statistical method conditions that have been adopted to verify the result of this research are as follows:

- Normality of data:

To assess the normality of the data, we tested the coefficients of skewness and kurtosis (Appendix 2). The results show that the data have satisfactory univariate normality.

- Homoscedasticity

The results of the Levene test (Appendix 2), which are based on the differences between the medians of the variables (Personalization/Performance Expectancy/Effort Expectancy/-Hedonic Motivation/Social Influence/Value Price/Habit/Usage Intention), are not significant ($p > 0.05$). This means that the variances of these variables are approximately equal, and that the homoscedasticity hypothesis is accepted.

For the variable “perceived confidentiality”, the results of the variance homogeneity test based on means and medians are significant ($p=0.041$; $p=0.046 \leq 0.05$). In this case, we can use Hartley’s Fmax to assess homoscedasticity. The variance ratio is therefore 1.065 /0.930=

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1.14. This difference is practically equal to 1, which means that the variances of the two samples are approximately equal. Therefore, the homoscedasticity hypothesis is also accepted for the variable "perceived confidentiality".

The apps are manipulated so that respondents are exposed to one (personalized) app or one (non-personalized) app. Respondents were then asked to indicate the degree of personalization of the application displayed, using a five-point Likert scale. A test of significance and comparison of the averages makes it possible to verify that these objectives were achieved (Table 1).

Table1. T-test for comparison of means of the degree of perceived personalization

Variable	Two-sided significance	Means B (without Personalization)	Means A (with Personalization)
Personalization measure	0.001	2.29	2.52

This result shows a significant difference (sig=0.001<0.05) between the means of the personalization measurement, which goes from a value of 2.29 for questionnaire "B" (non-personalized application) to a value of 2.52 for questionnaire "A" (personalized application). We can therefore deduce that the manipulation is correctly perceived by the respondents.

Experimental results

Table 2. Comparison of means

Variable		N	Mean	F	Sig.
Perceived personalization	A	489	2.52	12.027	0.001
	B	497	2.29		
PE (Performance Expectancy)	A	489	1.01	1.118	0.291
	B	497	1.06		
EE (Effort Expectancy)	A	489	0.93	3.364	0.067
	B	497	1.02		
FC (Facilitating Conditions)	A	489	1.14	12.712	0.000
	B	497	1.32		
HM (Hedonic Motivation)	A	489	0.40	8.409	0.004
	B	497	0.25		
SI (Social Influence)	A	489	0.65	0.341	0.559
	B	497	0.62		
PC (Perceived confidentiality)	A	489	0.57	4.256	0.039
	B	497	0.45		
PV (Price Value)	A	489	0.26	0.005	0.943
	B	497	0.26		
HABIT (Habit)	A	489	0.74	1.853	0.174
	B	497	0.81		
INTENTION (Intention to use)	A	489	0.87	6.857	0.009
	B	497	1.00		

For the variable "intention to use", the result shows that there is a significant difference between the means (F=6.857, sig.=0.009<0.05). Thus, personalization based on new technologies has an impact on the intention to use.

http://doi.org/10.18080/jtde.v12n1.891

Table 2 also shows that there is a significant difference between the means of the variables "hedonic motivation" (F=8.409, sig.=0.004<0.05). This finding confirms that personalization based on new technologies has an impact on hedonic motivation.

Concerning the perceived confidentiality variable, the results show that there is a significant difference between the means of the variables (F=4.256; sig.=0.039). Personalization based on new technologies has therefore an impact on perceived confidentiality.

For the variable "facilitating conditions", the results of Table 2 show that there is a significant difference between the means of the variables (F=12.712; sig.=0.000). This shows that personalization based on new technologies has an impact on facilitating conditions.

In addition, the results of Table 2 show that there is no significant difference between the means of the variables "performance expectancy", "effort expectancy", "social influence", "price value", and "habit". As a result, hypotheses H2-1, H3-1, H5-1, H7-1, and H8-1 are rejected. Consequently, the hypotheses concerning gender (H2-2, H3-2, H5-2, H7-2, H8-2), and age (H2-3, H3-3, H5-3, H7-3, H8-3) are rejected.

Structural Equation Modelling Analysis and Validation of the Theoretical Framework

In the next step, we tested the size and the sign of the impact of personalization on the variables that were retained from the experience. The retained variables are: intention to use, hedonic motivation, facilitating conditions, and perceived confidentiality. In this case, we refer to sample "A" (personalized application).

Method

Based on the experimental results, the SEM analysis was pursued to assess, firstly, the direct relationships presented in the theoretical framework and confirmed with the experiment; and, secondly, the moderating variables that were argued in the theoretical part. First, we describe sample "A" for which the questionnaire that included personalized application was administered. Then, we present the measurement scales of the retained concept. Next, we perform confirmatory factor analysis to evaluate the validity of the variables. Finally, we analyze the results of the direct and indirect relationships in the research model. These analyses are performed with SPSS 23 and AMOS22.

Descriptive statistics

Sample "A" is composed of 489 participants, mostly women (63.8%), while men represent (36.2%). In terms of age, the respondents are divided into three age groups. Respondents

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under 30 years old represent 44.8%, those between 30 and 50 years old represent 38.4% of the total sample, and those over 50 years old represent 16.8%. Finally, the socioeconomic categories are well represented in the sample. It is noted that a good part of the respondents is made up of Managers, Engineers, Technicians, Teachers, and Administrators (47.6%), followed by Students (27%), and Self-employed professionals (5.7%). Business owners and managers represent 3.3%. Workers represent 4.3%, the unemployed represent 7.8%, and, finally, retirees represent 4.3%. These statistics are shown in Table 3.

Table 3. Demographic profile of the participants

Demographic variable	**Sub-category**	**Frequency**	**Proportion (%)**
Gender	Male	177	36,2
	Female	312	63,8
Age	Under 30 years old	219	44,8
	Between 30 and 50 years old	188	38,4
	Over 50 years old	82	16,8
Profession	Student	132	27,0
	Unskilled worker	21	4,3
	Engineer, technician, teacher, administrator	233	47,6
	Business owner, manager	16	3,3
	Self-employed professional (lawyer, doctor, etc.)	28	5,7
	Retired	21	4,3
	Unemployed	38	7,8

Measurement scales and reliability

According to Malhotra *et al.* (2017), measurement model validity depends on reliability, the quality of fit indices, and evidence of construct validity, particularly convergent and discriminant validity.

Table 4 summarizes the main results of reliability, in addition to the main references used to retain these measurement scales and the related reliability indicators. The exploratory analysis in Table 4 shows good results for all measurement scales adopted in this research. We used SPSS 23 and AMOS 22 to conduct our statistical analyses.

Table 4. Measurement scales, references and main reliability indicators

Measurement scales		**Reliability analysis (of this study)**		**Previous studies**	
Variable	Number of items	Cronbach's alpha	Jöreskog's rho	Authors and context	Reliability index
Personalization	3	0.858	0.861	Xu *et al.* (2011) (location-aware marketing)	0.80
				Albashrawi & Motiwalla (2015) (M-banking)	0.920
Effort Expectancy	4	0.911	0.913	Venkatesh *et al.* (2012) (Information technology)	0.910
				Baabdullah *et al.* (2019) (M-banking)	0.867

Measurement scales		Reliability analysis (of this study)		Previous studies	
Variable	Number of items	Cronbach's alpha	Jöreskog's rho	Authors and context	Reliability index
Performance Expectancy	4	0.811	0.811	Venkatesh *et al.* (2012) (Information technology)	0.880
				Baabdullah *et al.* (2019) (M-banking)	0.897
Facilitating Conditions	3	0.750	0.758	Venkatesh *et al.* (2012) (Information technology)	0.750
				Baabdullah *et al.* (2019) (M-banking)	0.802
Hedonic Motivation	3	0.799	0.798	Venkatesh *et al.* (2012) (Information technology)	0.860
				Baabdullah *et al.* (2019) (M-banking)	0.750
Social Influence	3	0.853	0.857	Venkatesh *et al.* (2012) (Information technology)	0.820
				Baabdullah *et al.* (2019) (M-banking)	0.869
Price Value	6	0.850	0.883	Venkatesh *et al.* (2012) (Information technology)	0.85
				Baabdullah *et al.* (2019) (M-banking)	0.766
				Hariyanti *et al.* (2020) (M-banking)	>0.6
Habit	4	0.840	0.846	Venkatesh *et al.* (2012) (Information technology)	0.820
				Baabdullah *et al.* (2019) (M-banking)	0.759
Perceived Confidentiality	6	0.883	0.876	Casaló *et al.* (2007) (E-banking)	0.88
				Baabdullah *et al.* (2019) (M-banking)	0.857

Results of the Structural Equation Modelling (SEM)

The Chi-square (χ^2) test gives a ratio of less than 5 (Schumacker & Lomax, 2004). The GFI, AGFI, CFI, and TLI indices are close to 1. The RMR value does not exceed 0.1, and the RMSEA is significant, since it remains less than 0.08. The parsimony indices are between 0 and 1 (Malhotra *et al.*, 2017). Overall, the quality of fit can be considered acceptable. The results are presented in Table 5.

Table 5. Global model fit indices

Index	Absolute Indices				Incremental indices			Parsimony Indices		
	GFI	AGFI	RMR	RMSEA	TLI	NFI	CFI	PGFI	PNFI	Chi-squared (χ^2)
Model Value	0.909	0.880	0.066	0.077	0.915	0.905	0.927	0.688	0.776	3.858

The convergent validity of the variables in the model is satisfactory, because the average variance extracted (AVE) for each dimension is greater than 0.5, which is the generally accepted threshold for convergent validity. Regarding discriminant validity, we verified that the square root of the AVE of each construct exceeded its maximum correlation with any other construct. This implies that there is no correlation between the different variables (Malhotra *et al.*, 2017).

Table 6. Convergent and discriminant validity

	AVE	Personalization	FC	HM	PC	INTENTION
Personalization	0.691	**0.831**				
FC	0.572	0.463***	**0.756**			
HM	0.594	0.435***	0.540***	**0.771**		
PC	0.626	0.389***	0.439***	0.539***	**0.791**	
INTENTION	0.635	0.502***	0.711***	0.582***	0.554***	**0.797**

*** Significant at the 5% level

Results for direct relationships

The results of hypothesis testing for direct relationships between variables are presented in Table 7. Personalization based on new technologies has a positive impact on the intention to use M-Banking services (β = 0.805, t = 14.449, p = 0.000) and, therefore, H1 was accepted. Similarly, the results show that personalization based on new technologies has a positive impact on the variables facilitating conditions (β = 0.750, t = 13.077, p = 0.000), hedonic motivation (β = 0.694, t = 12.527, p = 0.000), and perceived confidentiality (β = 0.631, t = 10.730, p = 0.000). Thus, H1, H4-1, H6-1, and H9-1 are accepted, respectively.

Table 7. Structural equation model path analysis results

	Estimate (β)	S.E.	C.R. (T)	P
INTENTION <--- Personalization	0.805	0.063	14.449	***
FC <--- Personalization	0.750	0.061	13.077	***
HM <--- Personalization	0.694	0.063	12.527	***
PC <--- Personalization	0.631	0.069	10.730	***

*** Significant at the 5% level

Results for indirect relationships

In order to test the moderating role, we used complete invariance multi-group analysis (in Amos 22). The calculation of the Chi-squared difference test allows the determination of a probability level that will be compared to the recommended minimum threshold of 5%.

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For the gender variable, Table 8 shows that the Chi-squared value is not significant (p=0, 0.11>0.05). Thus, gender has no moderation impact between personalization and the variables facilitating conditions, hedonic motivation, and perceived confidentiality. Therefore, hypotheses H4-2, H6-2, H9-2, are rejected.

Table 8. Chi-squared difference test for gender

Chi-squared difference test			
	Chi-Squared	**Df**	**P**
Model 0 (constant model)	468.37	117	0.00%
Model 1 (free model)	456.83	110	0.00%
Chi-Squared	11.54	7	11.67%

Concerning the age variable, Table 9 shows that the Chi-squared test is significant between age groups. (p=0.0002<0.05). Thus, age has a moderation impact between personalization and the variables facilitating conditions, hedonic motivation, and perceived confidentiality. Therefore, hypotheses H4-3, H6-3, H9-3, are accepted.

Table 9. Chi-squared difference test for age

Chi-square difference test			
	Chi-Squared	**Df**	**P**
Model 0 (constant model)	547.65	187	0.00%
Model 1 (free model)	575.67	194	0.00%
Chi-Squared	28.02	7	0.02%

Table 10 represents the statistical results of the differences between age groups (below 30; 30-50; above 50). Indeed, we can deduce from Table 10 that personalization showed a stronger effect on the variables FC, MH and CP among the youngest respondents, as the "C.R." values for this age group are consistently larger than for the older age groups.

Table 10. Statistical results of the differences between age groups

	Below 30			**30–50**			**Above 50**		
	Estimate	S.E.	C.R.	Estimate	S.E.	C.R.	Estimate	S.E.	C.R.
FC <--- Personalization	0.372	0.056	6.615	0.354	0.079	4.494	0.431	0.096	4.507
PC <--- Personalization	0.420	0.061	6.857	0.307	0.081	3.799	0.339	0.116	2.919
HM <--- Personalization	0.429	0.054	7.959	0.262	0.074	3.537	0.383	0.123	3.125

Discussion

This study investigated how personalization based on new technologies influences individuals' intention to use mobile banking services, referring to the UTAUT2 model, which was extended with perceived confidentiality and moderated by age and gender. Overall, our findings show that personalization has an impact on the intention to use. This research converges with the study by Salem et al. (2019), which states that the use of Internet banking is positively related to customers' value for online personalization. The results show that users appreciate personalized mobile banking applications, they think that these services are practical and adapted to their needs and preferences.

Furthermore, in line with the findings of the study by Siyal et al. (2024) in the context of mobile commerce applications, this research admits that personalization based on new technologies has a positive impact on facilitating conditions. This shows that the personalized offer (credit card) that was displayed on the mobile application provided more information about facilitating conditions of using this service. Thus, new technologies such as intelligence and recommendation systems can constitute additional resources for the use of mobile banking applications. Personalization was found to have a stronger effect on the youngest respondents' facilitating conditions when compared to the older studied group.

In contrast to the study by Wang et al. (2017), which was conducted in the context of e-banking, our study found that personalization does not affect performance expectancy or effort expectancy. Indeed, participants do not perceive personalized mobile applications as a technology that provides them with benefits in terms of usefulness and ease of use.

In addition, our study proves that personalization based on new technologies has an impact on hedonic motivation. This result indicates that participants place more importance on emotional benefits. Indeed, their reaction to the design of the personalized application made them feel feelings of amusement or pleasure. This result confirms the finding of Riegger et al. (2021), who discovered that consumers perceive intrinsic satisfaction from technology-based personalization (TEP) in stores, particularly due to the positive emotions associated with personal recognition and affirmation. Indeed, we admit that personalization showed a stronger effect on the variables HM among the youngest respondents.

Concerning the perceived confidentiality variable, the results show that personalization based on new technologies has an impact on perceived confidentiality. This result indicates that the participants, more precisely the young respondents, believe that the bank can guarantee the confidentiality of their personal data, in order to offer relevant information adapted to their preferences. When compared with the study of Ho & Kwok (2002), which admits that privacy concerns related to personalization discourage customers from turning to a mobile commerce service provider offering personalized services, it is understandable that the context of banking services could provide more perceived confidence and data privacy precautions than other mobile commerce applications.

Conclusion and Recommendations

This study consists of an experiment that aimed to study the impact of technology-enabled personalization, along with gender and age, on the adoption factors and the intention to use mobile banking services. Results prove that personalization has a positive impact on hedonic motivation and a negative impact on performance expectancy and effort expectancy in the context of mobile banking applications. Findings show that respondents perceive personalized mobile applications as a technology that brings them hedonic benefits rather than usability and functionality benefits. Based on this research, mobile banking applications based on new technologies are expected to provide personalized services tailored to the aesthetic and emotional needs of users. This can help accelerate emotional engagement and attachment to the services offered.

The efforts of this research highlight the considerable role of technologies that enable personalization, to implement segmentation, targeting and positioning strategies in terms of age and gender. Indeed, personalization has been shown to have a stronger effect on the enabling conditions of younger respondents than older respondents. Then, the use of personalized mobile banking services based on new technologies could intensify their feeling of joy and entertainment. Moreover, results show that younger people do not have a problem to share their confidential information to obtain personalized banking services. This study could orient banks to compare the adoption factors of mobile applications for different user groups in order to tailor effective marketing decisions for each segment.

Concerning future research, we suggest the use of advanced data analytic methods like clustering and text-mining techniques to analyze large databases of customers' comments or e-mails regarding the use of mobile applications (Benslama & Jallouli, 2020; Chebil *et al.*, 2021). Another recommendation for future work suggests adopting this research experimental method for more mobile banking services, such as personalized real-time location services.

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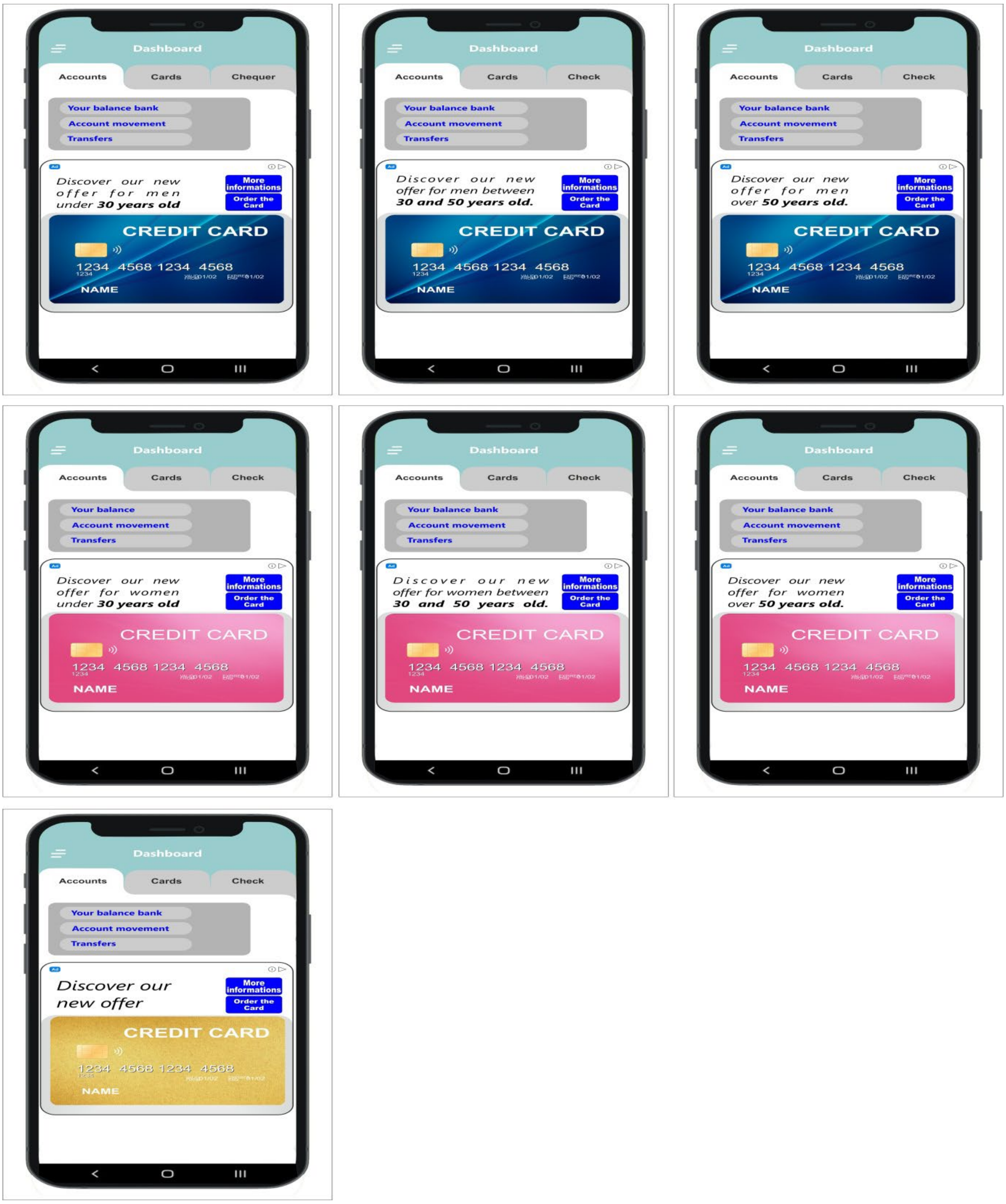
Appendix 1. Simulation of the mobile banking application



Appendix 2. Normality of data and Homoscedasticity

Normality of data

Features			
		Statistics	Standard error
Mobile banking apps provide personalized services tailored to the user's needs.	skewness	-.767	.074
	Kurtosis	-.082	.148
Mobile banking apps provide relevant information tailored to the user's preferences.	skewness	-.747	.074
	Kurtosis	-.019	.148
Mobile banking apps provide convenient services that the user enjoys.	skewness	-.829	.074
	Kurtosis	.099	.148
I find that this app is useful in everyday life (you can use it anywhere and anytime).	skewness	-1.413	.074
	Kurtosis	2.432	.148
This app increases the chances of accomplishing tasks that are important (for example. making transactions and transfers between banks).	skewness	-1.266	.074
	Kurtosis	2.153	.148
This app helps to accomplish tasks quickly and easily.	skewness	-1.355	.074
	Kurtosis	2.381	.148
Using this app increases efficiency.	skewness	-.736	.074
	Kurtosis	.194	.148
Learning how to use this app is easy.	skewness	-1.233	.074
	Kurtosis	1.856	.148
The interaction with this app is clear and understandable.	skewness	-1.217	.074
	Kurtosis	1.896	.148
This app is easy to use	skewness	-1.222	.074
	Kurtosis	2.082	.148
It is easy to master this app.	skewness	-1.215	.074
	Kurtosis	2.102	.148
I have the necessary resources (mobile phone and Internet) to use this app.	skewness	-1.633	.074
	Kurtosis	3.787	.148
I have the necessary knowledge to use this app.	skewness	-1.400	.074
	Kurtosis	1.846	.148
I can get help when I have difficulty using this app.	skewness	-.809	.074
	Kurtosis	.094	.148
Using this app is fun.	skewness	-.510	.074
	Kurtosis	-.234	.148
Using this app is enjoyable.	skewness	-.753	.074
	Kurtosis	.556	.148
Using this app is entertaining.	skewness	-.382	.074
	Kurtosis	-.078	.148
People who are important to me think it is necessary to use mobile banking apps.	skewness	-.783	.074
	Kurtosis	.190	.148
People who influence me think it is necessary to use mobile banking apps.	skewness	-.634	.074
	Kurtosis	-.041	.148
People whose opinions I value prefer that I use a mobile banking app.	Asymmetry	-.760	.074
	Kurtosis	.475	.148
I think banks care about the privacy of their mobile app users.	skewness	-.758	.074
	Kurtosis	.050	.148
I feel safe when I send personal information using this app.	skewness	-.475	.074
	Kurtosis	-.724	.148
I think mobile banking apps comply with data privacy laws.	skewness	-.682	.074
	Kurtosis	-.177	.148
I think mobile banking apps only collect the user's personal data that is necessary for its operation.	skewness	-.683	.074
	Kurtosis	-.168	.148
I think mobile banking apps respect the user's rights when obtaining personal information.	skewness	-.712	.074
	Kurtosis	-.020	.148
I think the bank will not provide my personal information (entered when using mobile banking services) to other companies without my consent.	skewness	-.630	.074
	Kurtosis	-.137	.148
By using mobile banking apps, I can save money (because I don't need to go to the bank).	skewness	-.974	.074
	Kurtosis	.330	.148

Features			
		Statistics	Standard error
Mobile banking apps are reasonably priced.	skewness	-.330	.074
	Kurtosis	-.769	.148
Mobile banking apps offer good value for money.	skewness	-.289	.074
	Kurtosis	-.708	.148
At the current price, mobile banking apps offer good value.	skewness	-.517	.074
	Kurtosis	-.319	.148
I have no concerns about the cost of Internet when using mobile banking apps.	skewness	-.754	.074
	Kurtosis	-.240	.148
The cost of using mobile banking apps is not burdensome for me.	skewness	-.562	.074
	skewness	-.467	.148
Using mobile banking apps has become/can become a habit for me.	skewness	-1.080	.074
	Kurtosis	.733	.148
Using mobile banking apps has become/can become an addiction for me.	skewness	.004	.074
	Kurtosis	-1.102	.148
I must use mobile banking apps.	skewness	-.790	.074
	Kurtosis	-.125	.148
Using mobile banking apps has become/can become natural for me.	skewness	-1.168	.074
	Kurtosis	1.592	.148
I intend to use mobile banking apps in the future.	skewness	-1.307	.074
	Kurtosis	2.281	.148
I will try to use mobile banking apps frequently in my everyday life.	skewness	-1.099	.074
	Kurtosis	1.196	.148
I plan to use mobile banking apps frequently.	skewness	-.954	.074
	Kurtosis	.757	.148
I will recommend mobile banking apps to other people.	skewness	-1.061	.074
	Kurtosis	1.106	.148

Homoscedasticity: Levene test

Variance homogeneity test					
		Levene's test	ddl1	ddl2	Sig.
Personalization	Based on mean	.507	1	1056	.477
	Based on median	.916	1	1056	.339
Performance expectancy	Based on mean	.615	1	1056	.433
	Based on median	.151	1	1056	.698
Effort expectancy	Based on mean	2.502	1	1056	.114
	Based on median	1.057	1	1056	.304
Facilitating conditions	Based on mean	.374	1	1056	.541
	Based on median	.160	1	1056	.689
Hedonic motivation	Based on mean	1.778	1	1056	.183
	Based on median	1.823	1	1056	.177
Social influence	Based on mean	1.461	1	1056	.227
	Based on median	1.344	1	1056	.247
Perceived confidentiality	Based on mean	4.762	1	1056	.029
	Based on median	4.777	1	1056	.029
Price value	Based on mean	.915	1	1056	.339
	Based on median	1.100	1	1056	.294
Habit	Based on mean	1.047	1	1056	.306
	Based on median	.499	1	1056	.480
Intention to use	Based on mean	.003	1	1056	.958
	Based on median	.876	1	1056	.350

Determinant Factors of Islamic Financial Technology Acceptance

Evidence from Indonesia

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Abstract: The rapid development of the Islamic-based financial industry in Indonesia has not been followed by the development of Islamic Financial Technology (iFinTech). This certainly raises questions about what factors affect iFinTech acceptance in Indonesia. In this study, the Technology Acceptance Model (TAM) was applied to identify the determinant factors of iFinTech acceptance. In this regard, five factors were identified as the determinant factors of iFinTech acceptance, namely perceived ease of use, perceived usefulness, subjective norm, self-efficacy, and customer innovativeness. Using an online questionnaire, this study gathered 526 responses from people who lived in various areas of Indonesia. Data were analyzed by a Structural Equation Model, and it was found that, among the five variables investigated, four variables, which are perceived usefulness, subjective norm, self-efficacy, and customer innovativeness, have significant influence on iFinTech acceptance; while perceive ease of use was found have no effect on iFinTech acceptance. This result is expected to be an input for related parties, such as iFinTech providers and the government, in making policies to encourage the development of the iFinTech industry in Indonesia.

Keywords: Islamic Literacy, Financial Technology, TAM, Islamic FinTech

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Introduction

As one of the countries with the largest Muslim population in the world, it is not surprising that, in Indonesia, the Islamic based financial industry is developing very rapidly. Currently, Indonesia is in second position in terms of the Islamic Financial Development Indicator (IFDI) index. In 2019, Indonesia was ranked number one in the world in this index, outperforming Malaysia and the United Arab Emirates (OJK, 2020). As commonly known, the IFDI index is a measure of a country's development of the Islamic financial industry. Hence, the score of the index reflects the growth of the Islamic financial industry in a certain country, in terms of both numbers and governance (IFD, 2020).

Based on the report of the Indonesian Financial Services Authority (OJK, 2020), the position of Indonesia in the global Islamic financial economy is the seventh position in the world regarding total Islamic financial assets. Indonesia also occupies the fourth position in the Global Islamic Economic Indicator (GIEI) ranking.

However, although the development of the Islamic financial industry in Indonesia is very encouraging, this development has not been followed by the development of Islamic Financial Technology or Islamic FinTech (Bank Indonesia, 2021). As mentioned by Muryanto *et al.* (2022), the number of iFinTech trade transactions in Indonesia is still lagging compared to other countries, such as Saudi Arabia, Iran, the United Arab Emirates, and Malaysia. In line with this, based on data from the Global Islamic FinTech (GIFT) index, Indonesia's score is 66 points, below Malaysia (87), Saudi Arabia (76), and the United Arab Emirates (70). The GIFT index shows which countries are most conducive to the growth of iFinTech.

This condition certainly needs attention from all parties, including academics. This is because the role of FinTech in contributing to the Islamic financial industry, such as banking, capital markets and non-bank financial industries, is very significant (Miskam *et al.*, 2019). In this digital era, the existence of FinTech in the Islamic financial industry is inevitable (Hui *et al.*, 2019). Furthermore, Hudaefi (2020) also mentioned that FinTech plays an essential role in the Islamic social finance and microfinance systems and supports the industry halal. It is even mentioned that Islamic FinTech also contributes to poverty alleviation (Hudaefi, 2020; Muryanto *et al.*, 2022).

Therefore, it is not surprising that the Government is very serious and pays great attention to the development of the Islamic economy, including the development of Islamic FinTech. It can be seen from the vision set by the Government through the Ministry of National Development Planning or the National Development Planning Agency in Indonesia's sharia economic masterplan for 2019-2024, namely to become "an independent, prosperous and civilized

Indonesia by becoming the world's leading Islamic economic center" (Kementrian Perencanaan Pembangunan Nasional, 2019).

In order to support government programs and policies related to the development of the Islamic financial industry, empirical studies are certainly needed regarding the acceptance of Islamic FinTech in the community, especially in Indonesia. However, until now, research and studies that discuss the acceptance of Islamic FinTech are still very limited in number (Alsmadi *et al.*, 2023; Majid, 2021). This condition also occurred in Indonesia, in which *iFinTech* studies are still rarely found (Hudaefi *et al.*, 2023).

In addition, the limited research on Islamic FinTech will certainly have an impact on the limited public understanding of Islamic FinTech. This condition is certainly an opportunity for researchers to conduct research on the acceptance of Islamic FinTech.

Therefore, this study aims to examine the determinant factors of iFinTech acceptance in Indonesia. Literature shows that there are several theories used in related studies regarding the level of acceptance of innovation or technology, one of which is the Technology Acceptance Model (TAM). TAM is a theory that is specifically developed to examine the level of acceptance of a technology, so it is not surprisingly that this theory is widely used in studies related to the adoption of technological innovations (Rahayu & Day, 2015; 2017). TAM was originally developed by Davis *et al.* (1989) to explain the factors that determine the acceptance of computer technology. In the initial model, there were two influencing factors, namely Perceived usefulness and perceived ease of use. Furthermore, this TAM was developed into TAM 3, where one of the variables, subjective norm, was included as one of the determining factors in the level of acceptance of technology (Venkatesh & Bala, 2008).

Several previous studies then used this TAM to investigate Islamic FinTech, namely Ali *et al.* (2021), Majid (2021), Nurfadilah & Samidi (2021) and Darmansyah *et al.* (2020). These researchers found that factors such as perceived usefulness, perceived ease of use, and subjective norm are determinant factors of the level of acceptance of Islamic FinTech. Therefore, in this study these three variables are also considered as determining factors for the level of acceptance of Islamic FinTech in Indonesia. In addition to these three variables, this study also tries to expand this TAM by adding variables of customer innovativeness and self-efficacy as determining factors in the level of acceptance of Islamic FinTech in Indonesia.

Customer innovativeness is added because several studies related to the level of acceptance of technological innovation find that customer innovativeness is also one of the determining factors in the adoption of information technology. For example, Rahayu & Day (2015), Ghobakhloo *et al.* (2011) and Ghobakhloo & Tang (2013) found that a person's innovativeness is one of the determining factors of e-commerce adoption. Lassar *et al.* (2005) also found that customer innovativeness is an important factor influencing the acceptance of online banking systems, as well as Lee *et al*. (2007), who found that customer intention to travel may change with regards to innovativeness level and in a similar vein. This is in line with the theory of diffusion of innovation presented by Rogers (2002), which states that innovative consumers tend to be in the category of innovators or early adopters.

In addition to customer innovativeness, self-efficacy, which is a person's belief in his/her ability to perform a task to achieve a certain goal (Luszczynska & Schwarzer, 2015), is also an important factor that influences one's behaviour. This is explained in the social cognitive theory developed by Bandura (1977), which states that a person's behaviour or actions will be greatly influenced by forethought. Previous research has also used this variable as a factor that affects the level of acceptance of a technological innovation (Shaikh *et al*., 2018). Shaikh *et al*., (2018) found that self-efficacy is an important factor that affects student intention in using the computing resource centre. Hence, based on the explanation above, this study will try to analyse the level of acceptance of Islamic FinTech using TAM with two added variables, customer innovativeness and self-efficacy, as determinant factors of Islamic FinTech in Indonesia.

The paper is organized into several sections. It begins with an introduction section that introduces the key research question. This is followed by a literature review section that delves into relevant research and formulates the hypotheses. Next comes the research methods section, which details how the research was conducted. Then, the results and discussion section presents and discusses the research findings. Finally, the conclusion and suggestion section interprets the results and highlights their implications.

Literature Review

Islamic FinTech

Financial Technology or FinTech is a combination of financial services with digital technology services (Morgan *et al*., 2019; Setiawan *et al*., 2020; Rahayu *et al*., 2022b, Rahayu *et al*., 2023). This technology has changed the business practices of conventional financial businesses to be automated (Feyen *et al*., 2021). Meanwhile, Islamic FinTech is defined by Hudaefi (2020) as an innovative financial industry that uses technology to increase financial activities that offer products and services in accordance with Sharia, advocate the *Maqa'sid* al Shariah (objective of Islamic law), and apply the *fatwa* (juristic opinion) and rules.

From the definition above, it can be seen that the main difference between conventional FinTech and Islamic FinTech is the underlying principle, in which Islamic FinTech must follow Islamic financial rules, such as the prohibition of *Riba* (usury), *Gharar* and *Maisir*. The term

Riba (usury) in Arabic means "addition": usury is defined as the excess paid by the borrower to the lender for the use of money (Marhaini *et al.*, 2005). *Gharar* is uncertainty or lack of clarity in a transaction that can cause losses for one or both parties (Rudiansyah, 2020). *Maisir* is gambling or betting that involves betting money or property with an uncertain outcome (Rudiansyah, 2020). Both *Gharar* and *Maisir* also are prohibited in Islam.

It is commonly known that, in conventional FinTech, these principles or prohibitions are not important things to consider when creating financial products or services. Therefore, for Muslims, some FinTech products and services, such as cryptocurrency, online gambling, and peer-to-peer lending, are not in accordance with Islamic principles. With the emergence of Islamic FinTech, this should be something that is attractive to Muslims, especially in providing alternative sources of financing as well as financial products and services.

In addition, Hudaefi (2020) revealed that Islamic FinTech is obliged to use sharia principles, such as the principle of *Murabaha* (cost plus financing), *Musharakah* (joint venture) and *Mudharabah* (partnership capital and labour). In general, Islamic FinTech is divided into five fields: social finance, insurance, asset management, deposits and loans, and financial services (Muryanto *et al.*, 2022). Furthermore, they mentioned that there are several types of Islamic FinTech in Indonesia: Sharia Peer-to-Peer lending (P2P); Payment, clearing and sharia settlement; Sharia E-aggregator and Risk Management; and Sharia Investment

Factors affecting Islamic fintech acceptance

As explained earlier, to examine the acceptance of Islamic FinTech, the Technology Acceptance Model (TAM) was used in this study. In TAM, several factors affect a person's acceptance of an innovation or technology, in this case, Islamic FinTech. These factors are perceived ease of use, perceived usefulness, subjective norms, self-efficacy, and customer innovation.

Perceived ease of use

Perceived ease of use is defined as the degree to which an individual believes that using technology does not require much effort (Davis *et al.*, 1989). Someone will be inclined to use or adopt certain innovation technology if the person feels that the innovation is easy to use. Previous studies, such as Rahayu (2022a) and Alwi *et al.* (2021), found that the perceived ease of use has a significant influence on a person's intention to use e-wallets. Furthermore, in regard to Islamic FinTech, Thaker *et al.* (2018) also found that the intention of a crowd-funder to use *crowdfunding-Waaf Model* is strongly influenced by perceived ease of use. Furthermore, Majid (2021) mentioned that perceived ease of use is also a determinant factor that affects MSMEs' intentions to use Islamic FinTech. This is also supported by research conducted by Shaikh *et al.* (2020) and Ali *et al.* (2021), which found that perceived ease of use has a significant influence on the level of acceptance of Islamic FinTech.

In this study, the perception of ease of use was identified as one factor determining a person's acceptance of Islamic FinTech. Based on the explanation above, it can be hypothesized that:

Hypothesis 1: Perceived Ease of Use has a significant influence on the acceptance of Islamic FinTech in Indonesia.

Perceived usefulness

Perceived usefulness is defined as the user's expectation of how an innovation or technology can improve performance and/or assist them in carrying out their work (Oliveira & Martins, 2010). In this case, if a person believes that an innovation or technology brings/provides benefits to themself or has an impact on improving their performance, then the individual tends to accept and adopt such innovations or technologies. Previous studies have tried to investigate the effect of perceive usefulness on intention to adopt an innovation technology, such as Rahayu & Day (2015), Ho *et al.* (2020), Ghobakhloo & Tang (2013), Alam *et al.* (2011), Ghobakhloo *et al.* (2011), and Oliveira & Martins (2010). They found that perceived usefulness is an important factor influencing a person's intention to adopt technology. In regard to Islamic FinTech, several such studies have also found that perceived usefulness has a significant influence on the acceptance of Islamic FinTech (Amin *et al.*, 2014; Shaikh *et al.*, 2020; Ali *et al.*, 2021). Based on the explanation above, it can be hypothesized that:

Hypothesis 2: Perceived usefulness has a significant influence on the acceptance of Islamic FinTech in Indonesia.

Subjective norm

Subjective norms are defined as an individual's attitude in the face of the social pressure he or she feels to do or not to do something (Ajzen, 1991). In this case, if a person feels that the surrounding environment, such as family or friends, encourages them to do something, then the individual is likely to do it. So, in this study Subjective Norms are also identified as one of the variables that affect acceptance of an innovation or technology, in this case Islamic FinTech.

Several previous studies have tried to test whether these subjective norms significantly influence the level of acceptance of an innovation or technology (Fauziah *et al.*, 2008; Alwi *et al.*, 2021). Fauziah *et al.* (2008) examined the influence of subjective norms on student intentions in Islamic housing. They found that subjective norms have a significant relationship with the intention of students to use Islamic housing. Meanwhile, Alwi *et al.* (2021) found that subjective norm as one of determinant factors of e-wallet adoption. Then, Amin *et al.* (2013)

and Lada *et al.* (2008) also conveyed the same thing. They found that subjective norms influence the behaviour intention of Islamic housing and halal products. In regard to Islamic FinTech, Darmansyah *et al.* (2020) and Majid (2021) revealed that subjective norm has significant influence on the intention to use Islamic FinTech. Therefore, based on the explanation above, in this study it can be hypothesized that:

Hypothesis 3: Subjective Norms have a significant influence on the acceptance of Islamic FinTech in Indonesia.

Self-efficacy

Luszczynska & Schwarzer (2015, p. 167) defined self-efficacy as "people's beliefs in their capabilities to perform a specific action required to attain a desired outcome". According to Social Cognitive Theory (Bandura, 1977), self-efficacy is an important factor that influences a person's behaviour. Self-efficacy influences behaviour through two mechanisms, namely motivation and ability. In this regard, high self-efficacy will encourage the individual to take action and strive hard to achieve a goal. Those who have high self-efficacy will certainly be more motivated in facing obstacles and challenges. In addition, individuals with high self-efficacy will also be more confident in developing their abilities (Luszczynska & Schwarzer, 2015).

Previous studies show that the self-efficacy is one of the determinant factors of innovation adoption (Shaikh *et al.*, 2018; Tamjidyamcholo *et al.*, 2013; Bradley *et al.*, 2017; Liu & Chou, 2020; Kongarchapatara & Rodjanatara, 2018). Shaikh *et al.* (2018) found that self-efficacy is one of the determinant factors of a student's intention to use the computing resource centre. Then, Tamjidyamcholo *et al.* (2013) found self-efficacy as a factor that influences the intention of information security workers to share knowledge. Similarly, Bradley *et al.* (2017) found that self-efficacy is one of the reliable factors for online course learning usage. In addition, Liu & Chou (2020) revealed that the higher a person's self-efficacy, the higher the likelihood of that person to adopt the use of smart household appliances. Similar results were also obtained by Kongarchapatara & Rodjanatara (2018), who found that self-efficacy indirectly affects the intention to use the QR Code Payment application. In regard to Islamic FinTech adoption, Shaikh *et al.* (2020) revealed that a person who has high self-efficacy (or high self-confidence) is more willing to accept Islamic FinTech. Therefore, based on the explanation above, it can be hypothesized in this study that:

Hypothesis 4: Self-efficacy has a significant influence on the acceptance of Islamic FinTech in Indonesia.

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Customer innovativeness

Innovativeness is defined by Rogers (1995) and Marcati *et al.* (2008) as a person's ability to adopt new ideas or ideas earlier than others in their environment. It is mentioned by Thong & Yap (1995) that an innovative manager will tend to find a solution by changing the structure in which the problem lies. In simple language, innovative managers tend to find solutions in a way no one else has done before, so that, when there is an innovation or a new technology, they tend to adopt it. Therefore, in this study, customer innovation was identified as a variable that affects the acceptance of Islamic FinTech in Indonesia. This is also supported by several studies that have found that innovativeness significantly influences the adoption and acceptance of technology (Liu & Chou, 2020; Hu *et al.*, 2019; Shahzad *et al.*, 2022). Furthermore, Shaikh *et al.* (2020) also found that customer innovativeness has an influence on public acceptance of Islamic FinTech.

Based on the explanation above, in this study it can be hypothesized that:

Hypothesis 5: Customer innovativeness has a significant influence on the acceptance of Islamic FinTech in Indonesia.

Conceptual model

Based on the explanation above, the conceptual model of this study is presented in Figure 1:

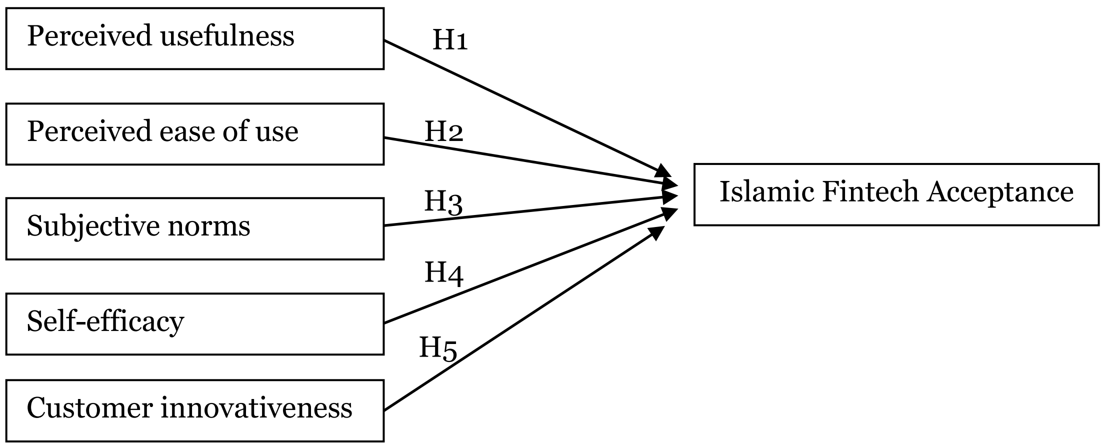

Figure 1. Conceptual Model

Research Method

This research uses a quantitative approach to explain the relationship between variables. The survey method using a structured questionnaire was chosen as a research strategy in this study. The survey method is one of the methods used to collect information from a person in order to explain their attitudes, knowledge, and behaviour (Sekaran & Bougie, 2013). In this study, the structured questionnaire was presented in a Google form. It was distributed to respondents using social media, such as WhatsApp, Instagram, and Facebook, and email, with

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snowball techniques. The population in this study is the entire community in Indonesia. However, because the total population of Indonesia is widely spread, we focus on people living on Sumatra and Java islands. Based on Indonesian Central Statistics Agency report in 2020 (BPS, 2020), it was shown that most of the Indonesian population was domiciled in the island of Java (56.10%) and the island of Sumatra (21.68%). So, it is considered that the residents on the two islands can be used to reflect the level of public acceptance of Islamic FinTech.

Variables and operational definitions of variables

In this study, several variables are measured and tested; these variables are described in Table 1.

Table 1. Operational Definitions of Variables

Variable	Number of Indicators	References
Islamic FinTech Acceptance: it refers to how eager a person is to do or use an information technology innovation, in this case, Islamic FinTech	5 questions	Davis *et al.* (1989); Venkatesh *et al.* (2003); Shaikh *et al.* (2020)
Perceive ease of use, a degree to which an individual believes that the use of technology, in this case is Islamic FinTech, does not require much effort	5 questions	Davis *et al.* (1989); Shaikh *et al.* (2020); Rahayu (2022)
Perceived usefulness, a degree to which a person believes that a new technology or innovation will be helpful or useful to them	6 questions	Davis *et al.* (1989); Ali *et al.* (2021); Shaikh *et al.*, (2020)
Subjective Norm, the attitude of an individual in the face of the social pressures to do or not to do something, in this case related with Islamic FinTech	4 questions	Ajzen (1991); Ali *et al.* (2021); Shaikh *et al.* (2020)
Self-efficacy, an individual's level of confidence in his or her ability to do something	4 questions	Shaikh *et al.* (2020)
Customer innovativeness, the degree of a person's ability to adopt new ideas or ideas earlier than others in their environment	4 questions	Rogers (1995); Rahayu & Day (2015)

Then, in this study, the data were processed using the Structural Equation Model (SEM). SEM was chosen as a data processing method because it provides advantages compared to other methods, where in SEM we can do two things at once, namely factor analysis and regression or correlation analysis in one stage. In this case, SEM PLS is used as the statistical test tool.

Results and Discussion

Demographic characteristics of respondents

In this study, 526 respondents participated. Table 2 shows the data related to the demographics of respondents who participated in this study.

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Table 2. Demographic Characteristics of Respondents

Gender	**Frequency**	**Percentage**
Man	156	29.66%
Woman	370	70.34%
Total	*526*	*100%*
Age		
Ages 15- 20	235	45%
21 years old - 25 years old	202	38%
Ages 26 to 30	17	3%
ages 31 to 35	35	7%
Ages 36 to 40	25	5%
Ages 41 to 45	7	1%
Ages 46 to 50	1	0.19%
Ages 51 and up	4	1%
Total	*526*	*100%*
Employment Status		
Working	96	18.25%
Student	413	78.52%
Not Working	17	3.23%
Total	*526*	*100%*
Recent Education		
High-school equivalents	358	68.06%
Diploma I, II, III	52	9.89%
Bachelor/Diploma IV	103	19.58%
Master/S2	9	1.71%
Doctor/S3	4	0.76%
Total	*526*	*100%*
Marital Status		
Unmarried	440	83.65%
Married	69	13.12%
Divorced	17	3.23%
Total	*526*	*100%*
Religion		
Buddhism	3	0.57%
Hinduism	1	0.19%
Islam	499	94.87%
Catholic Christianity	8	1.52%
Protestant Christianity	15	2.85%
Total	*526*	*100%*

Table 2 shows that most of the respondents who participated in this study were respondents with a female gender (70.34%), while the rest were men (29.66%). In terms of age, the age range of respondents participating in this study varied from 15 to over 51 years of age, although most of them were respondents with ages 15 to 25 years. Judging from the employment status, of course, the majority are students; students with the last level of education being high school equivalent; and with unmarried. This is natural, because, indeed, the ages of 15 to 25 years in Indonesia still include school age and young age.

Furthermore, from Table 2, it can also be seen that most of the respondents in this study are Muslims. This condition is certainly not surprising, because Indonesia is indeed a country with a Muslim majority population.

As explained earlier, this questionnaire was distributed to people domiciled on the islands of Sumatra and Java. In this study, 144 respondents (27.37%) are domiciled in Java and 382 respondents (72.63%) are domiciled in Sumatera.

Experience using Islamic fintech

Based on the data obtained, it is known that, of the 526 respondents who participated in this study, 276 respondents or 52.47% of them had experience in using products from Islamic FinTech; while the rest, as many as 250 respondents or 47.53%, did not have experience in using an Islamic FinTech product. Some Islamic FinTech products that are widely used by respondents are shown in Table 3.

Table 3. Types of Islamic FinTech Products

Type of Islamic FinTech Product	Frequency	Percentage
PLink Aja Syariah	94	18.65%
BSI Mobile Banking	226	44.84%
Dompet Dhuafa	34	6.75%
Kita Bisa (Zakat)	43	8.53%
Indonesia Sharia Fund	32	6.35%
Rumah Zakat	41	8.13%
Ethics	4	0.79%
Natural	11	2.18%
Investee	8	1.59%
Amana	6	1.19%
Sharia Mutual Fund Investment	1	0.20%
M-Banking Bank Nagari Syariah	1	0.20%
Prudential	1	0.20%
Dana	2	0.40%

From Table 3, it can be seen that the most widely used products by respondents are mobile banking products from Islamic banks, followed by Link Aja Syariah digital wallet products; while other products, such as Kitabisa (for zakat payments) and zakat houses, are ranked 3rd and 4th most widely used. These are followed by other products, such as Dana Syariah Indonesia, Ethics, and others.

Data analysis

The data was processed using SEM PLS. In SEM there are 3 main stages, namely evaluation of measurement model (known as outer model), evaluation of model feasibility, and evaluation of structural models (hypothesis testing). In the evaluation of the measurement model, the validity and reliability tests have been conducted, and the results are presented in Table 4.

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Table 4. Validity and Reliability Test

Variable	Indicator	Loading Factor >0.7	Composite Reliability	Cronbach Alpha >0.6	Average Variance Extracted (AVE)>0.5
Islamic FinTech Acceptance (IFA)	IFA1	0.821	0.925	0.899	0.713
	IFA2	0.842			
	IFA3	0.858			
	IFA4	0.843			
	IFA5	0.856			
Customer Innovativeness (CI)	CI1	0.846	0.907	0.899	0.764
	CI2	0.915			
	CI3	0.861			
Perceived Ease of Use (PEOU)	PEOU1	0.789	0.935	0.916	0.706
	PEOU2	0.876			
	PEOU3	0.861			
	PEOU4	0.874			
	PEOU5	0.850			
	PEOU6	0.787			
Perceived usefulness (PU)	PU1	0.808	0.931	0.907	0.730
	PU2	0.865			
	PU3	0.865			
	PU4	0.875			
	PU5	0.858			
Self-efficacy (SE)	SE1	0.853	0.910	0.851	0.771
	SE2	0.896			
	SE3	0.885			
Subjective Norm (SN)	SN1	0.824	0.898	0.829	0.747
	SN2	0.912			
	SN3	0.855			

From Table 4, it can be seen that all requirements related to validity and reliability tests in this study have been met. Therefore, subsequent data processing, which is evaluation of the structural model, can be resumed. In this stage, the path coefficient test and the Goodness of Fit evaluation will be carried out. For the path coefficient test, results can be seen in Table 5.

Table 5. Path Coefficient

	Islamic FinTech Acceptance
Customer Innovativeness	0.301
Perceived Ease of Use	0.049
Perceived usefulness	0.250
Self-efficacy	0.196
Subjective Norm	0.164

The path coefficient test aims to see how strongly exogenous variables affect endogenous variables. From the Table 5, it can be seen that the customer innovativeness variable affects the acceptance rate of Islamic FinTech by 30.1%, while other variables, such as perceived ease of use, perceived usefulness, self-efficacy, and subjective norm affect the level of acceptance of Islamic FinTech by 4.9%, 25%, 19.6% and 16.4%, respectively. From the table, it can be seen that, of the five exogenous variables tested, the customer innovativeness variable has the greatest influence on the level of acceptance of Islamic FinTech by the public in Indonesia. This is followed by the variables perceived usefulness, self-efficacy, subjective norm, and, finally, the perceived ease of use.

In addition, in this study, a Goodness of Fit test was also carried out to see the feasibility of the research model. In this regard, the Normal Fit Index (NFI) and the Standardized Root Mean Square Residual (SRMR) value are used to identify the feasibility. According to Ghozali (2016), a model can be said to be good if it has an NFI value close to 1 and its SRMR value is smaller than 0.1. In addition, d_ULS and d_G also can be used to indicate the goodness of fit of the model. In this regard, values below 1 for d_ULS and d_G are desirable. The test results for NFI, SRMR, d_ULS and d_G can be seen in Table 6.

Table 6. Normal Fit Index and Standardized Root Mean Square Residual

	Saturated Model	Estimated Model
SRMR	0.048	0.048
d_ULS	0.747	0.747
d_G	0.455	0.455
Chi-Squared	1462.504	1462.504
NFI	0.858	0.858

From Table 6, it can be seen that the NFI value for this research model is 0.858, and this figure is a number close to 1. Further, Table 6 also shows that the SRMR value for this research model is 0.048, and this figure is smaller than 0.1. Then, the d_ULS and d_G values, which are 0.747 and 0.455, respectively, are also below 1. It can be concluded that this research model has met the criteria for goodness of fit.

In addition to looking at the NFI and SRMR values in this stage, the R squared values will also be seen. This R Squared value shows how much the change of the endogenous variable is caused by the change in the exogenous variables together. In this study, the R square value can be seen in Table 7.

Table 7. R squared

	R Squared	R Squared Adjusted
Islamic FinTech Acceptance	0.667	0.664

From Table 7, it can be seen that the R squared value in this study is 0.667. This figure shows that the variables of customer innovativeness, perceived ease of use, perceived usefulness, self-efficacy, and subjective norm are able to explain the change in the acceptance rate of Islamic FinTech by 66.7%. This figure according to Cohen (1988) can be categorized as a very influential or substantial number.

Hypothesis Testing

The next stage is the hypothesis testing stage. In this case, the results of hypothesis testing can be seen in Table 8.

Table 8. Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistic (|O/STDEV|)	P Value
Perceived Ease of Use -> Islamic FinTech Acceptance	0.049	0.048	0.045	1.093	0.275
Perceived Usefulness -> Islamic FinTech Acceptance	0.250	0.254	0.053	4.703	0.000
Subjective Norm -> Islamic FinTech Acceptance	0.164	0.167	0.045	3.680	0.000
Self-efficacy -> Islamic FinTech Acceptance	0.196	0.192	0.046	4.232	0.000
Customer Innovativeness -> Islamic FinTech Acceptance	0.301	0.300	0.049	6.092	0.000

According to Hair *et al.* (2017), if the p-value is smaller than 0.05 and/or the t statistic is larger than 1.96, then it can be concluded that the exogenous variable has a significant influence on the endogenous variable. From Table 8, it can be seen that, of the five variables tested, only one variable, namely the perceived ease of use variable, has a p-value larger than 0.05 and has a t statistic smaller than 1.96, while the other variables, customer innovativeness, perceived usefulness, self-efficacy, and subjective norm, have a p-value smaller than 0.05 and a statistical t value greater than 1.96. This shows that, in this study, of the five variables tested, only one variable did not have a significant influence on the level of acceptance of Islamic FinTech, while the other variables have a significant influence on the level of acceptance of Islamic FinTech. Therefore, in this study it can be concluded that Hypotheses 2, 3, 4 and 5 are supported, while Hypotheses 1 is rejected.

Discussion

The effect of perceived ease of use on the acceptance of Islamic FinTech in Indonesia

Based on Table 8, it can be seen that the p-value for the relationship between the perception of ease of use and acceptance of Islamic FinTech is 0.275, larger than 0.05, and the t statistic is 1.093, smaller than 1.96. These results indicate that statistically there is no significant influence between the perception of ease of use and the acceptance of Islamic FinTech. This certainly does not support the TAM theory proposed by Davis *et al.* (1989), which states that, if a person feels that a technological innovation is easy to use, then the individual is likely to accept and use the innovation. The results of this study are also different from the results of research conducted by Shaikh *et al.* (2020) and Ali *et al.* (2021), which found that the perception of ease of use is one of the determining factors of the level of acceptance of Islamic FinTech.

This difference in results may be due to the fact that most of the respondents in this study are generation Z who were born in the era of information technology, so when dealing with certain applications, especially applications based on information technology, it is certainly no longer a new and difficult thing for them, because they are used to the technology. Hence, the perception of ease of use is no longer a factor that determines their acceptance of a technological innovation.

The effect of perceived usefulness on the acceptance of Islamic FinTech in Indonesia

In terms of the influence of usability perceptions on the acceptance of Islamic FinTech, from Table 8, it can be seen that the p-value and t statistics are 0.00 and 4.703, which indicates that the variable perceived usefulness has a significant influence on the acceptance of Islamic FinTech in Indonesia. In this case, if an individual feels that a technological innovation (in this case it is Islamic FinTech) is useful and will help them in carrying out the work, then the level of acceptance of these technological innovations will also be higher; as we know that Islamic FinTech provides many conveniences for its users in carrying out various activities, ranging from online payment activities to investment activities.

This is in line with the theory presented by Davis *et al.* (1989) and Venkatesh & Davis (1996), which states that perceived usefulness is an important variable that affects a person's intention to use an innovative technology. The results of this study are also in line with previous studies, such as Amin *et al.* (2014), Shaikh *et al.* (2020), Ali *et al.* (2021) and Nurfadilah & Samidi (2021), which found that the perception of usability has a significant influence on FinTech acceptance.

The effect of subjective norm on the acceptance of Islamic FinTech in Indonesia

From Table 8 above, it can also be seen that the relationship between subjective norms and the acceptance rate of iFinTech has a p-value below 0.05 (i.e., 0.00) and a statistical t value above 1.96 (i.e., 3.68), which indicates that there is a significant influence of subjective norms on the level of acceptance of iFinTech by the public in Indonesia. As explained earlier, this subjective norm relates to the attitude of the individual in responding to the views/attitudes of the people around him or her; in this case, if the people think that iFinTech is the right choice in helping them carry out various activities, then the individual also tends to follow these views or attitudes. As we know that most Indonesians are Muslims, of course, in an environment where the majority of the population is Islamic, the public's view of iFinTech is positive, so their acceptance rate of this iFinTech product is also high.

This result certainly supports the Theory Acceptance Model (TAM) proposed by Davis *et al.* (1989) and Venkatesh & Davis (1996). These results are also in line with the results of research conducted by Majid (2021), Darmansyah *et al.* (2020), Thaker *et al.* (2019), Fauziah *et al.* (2008), Amin *et al.* (2013) and Lada *et al.* (2009).

The effect of self-efficacy on the acceptance of Islamic FinTech in Indonesia

In Table 8, it can be seen that the relationship between the influence of self-efficacy on the acceptance of iFinTech in Indonesia has a p-value of 0.00, which is smaller than 0.05, and a statistical t value of 4.232, which is greater than 1.96. This shows that statistically there is a significant influence of self-efficacy on the acceptance of iFinTech in Indonesia.

This self-efficacy shows the level of confidence of an individual to be able to do or use an innovation, in this case iFinTech. The study demonstrates a positive relationship between an individual's high self-efficacy and their increased acceptance of iFintech. The result indicates that individuals with greater confidence in their ability to adopt and use innovative financial technologies exhibit a high propensity for accepting iFintech.

The results of this study are consistent with the results of previous studies, such as those conducted by Shaikh *et al.* (2018), Kongarchapatara & Rodjanatara (2018) and Shaikh *et al.* (2020). In these cases, they found that self-efficacy has a significant influence on the level of acceptance of a technology.

The influence of customer innovativeness on the acceptance of Islamic FinTech in Indonesia

As with other variables, in this study customer innovativeness is also seen to be one of the determining factors that affect the level of acceptance of iFinTech in Indonesia. This can be seen from the p-value, 0.01, of the relationship between customer innovativeness and the iFinTech acceptance rate, which is smaller than 0.05, and a statistical t value of 3.680, which is more than 1.96. As explained earlier, an individual is categorized as innovative if the individual is able to adopt an idea or ideas earlier than others, so that innovative individuals will certainly be inclined to have a level of acceptance of new innovations, in this case iFinTech, which is higher than others. So, it is not surprising that in this study it was found that customer innovativeness has a significant influence on the level of acceptance of iFinTech in Indonesia. From Table 8, it can also be seen that, among the five variables tested in this study, namely perceived ease of use, perceive usefulness, self-efficacy, subjective norm and customer innovativeness, the variable customer innovativeness has the most influence, which is 30.1%.

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This figure indicates that the variable customer innovativeness affects the variable acceptance of iFinTech by 30.1%.

These results are in line with the results of research conducted by Lassar *et al.* (2005), Ho *et al.* (2020) and Hu *et al.* (2019), who found that customer innovativeness has a significant influence on the acceptance rate of technological innovations, including iFinTech. This is also in line with research conducted by Shaikh *et al.* (2020), which found that customer innovativeness has a significant influence on the level of acceptance of iFinTech.

Conclusions and Suggestions

Based on the explanation in the previous section, it can be concluded that, of the five variables identified as determinant variables in the acceptance of iFinTech, namely perceived ease of use, perceived usefulness, self-efficacy, subjective norm and customer innovativeness, only one variable does not have a significant influence on the level of acceptance of iFinTech in Indonesia, namely the perceived ease of use variable. Meanwhile, four other variables, namely perceived usefulness, self-efficacy, subjective norm and customer innovativeness, were found to have a significant influence on the level of acceptance of iFinTech in Indonesia.

This result can certainly be an input for decision-makers to be able to pay attention to these factors to increase public acceptance in Indonesia related to iFinTech. As we know, the number of trade transactions for iFinTech is still far below those of other countries, such as Saudi Arabia, the United Arab Emirates and Malaysia. On the other hand, we know that iFinTech has enormous potential in Indonesia considering that most of the population in Indonesia is Muslim. Something that the Government may be able to do in this case ids to get the Financial Services Authority to increase public acceptance of iFinTech products and services by socializing iFinTech with the public, so that there is a good level of understanding in the community, which will certainly encourage the use of iFinTech.

Furthermore, for iFinTech business providers, the results of this study can also be used as input in order to consider the usability factors in designing products or applications related to iFinTech. The product or feature that offers advantages will certainly attract individuals to adopt or use it. In addition, iFinTech business people also need to socialize their products with the public, because, as we know, the subjective norms that apply in society and self-efficacy turned out to be able to encourage the level of public acceptance of the iFinTech product.

Nevertheless, it is also undeniable that this study has its drawbacks, especially those related to the research sample. As explained in the previous section, most of the respondents in this study are from Sumatra; of course, this condition will affect the generalization of the results. In addition, most of the respondents in this study are generation z, which certainly has

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different characteristics from other generations, so it will also affect the generalization of results. Therefore, for subsequent studies, it would be necessary to expand the sample to other countries and to various ages.

This study has contributed to the literature by adding two other variables, customer innovativeness and self-efficacy, in testing determinant factors of Islamic FinTech. Interestingly, this study actually found that customer innovativeness and self-efficacy have a major influence on Islamic FinTech acceptance compared to other variables. Therefore, for future research, it may also be possible to consider these factors in investigating the level of acceptance of a technological innovation. In addition, this research also enriches the literature by conducting a study on Islamic FinTech acceptance in one of the developing countries that also has a large Muslim population. Studies related to Islamic FinTech are still rarely found, so this study could provide enlightenment to other researchers regarding the picture of the level of acceptance of Islamic FinTech in developing countries.

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Impact of Data Analytics Capabilities on CRM Systems' Effectiveness and Business Profitability

An Empirical Study in the Retail Industry

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Abstract: In the current digital era, understanding the role of Data Analytics Capabilities (DAC) in Customer Relationship Management (CRM) systems is essential for businesses seeking better decision-making. While DAC is acknowledged as a Critical Success Factor (CSF) for CRM systems, there is a gap in empirical evidence quantifying its effect on business profitability. This study aims to (1) present the conceptual foundation of the impact of DAC for CRM systems on marketing decisions and business profitability, and (2) empirically estimate the impact of integrating DAC on marketing performance and business profitability. Focusing on the retail sector, the study gathered 131 questionnaires from employees involved in CRM and DAC in Lebanon, and used the SPSS tool for data analysis. The research findings provide advanced empirical evidence of the importance of DAC as a CSF for CRM systems, alongside people, process, and technology dimensions. Results show that the integration of DAC represents a significant step forward in enhancing the effectiveness of CRM systems and achieving better business profitability. This study challenges the conventional understanding of technology's role in improving business outcomes, thus providing valuable theoretical and practical implications for organizations aiming to enhance their CRM systems.

Keywords: Data analytics capabilities, customer relationship management, critical success factors, business profitability, empirical evidence

Introduction

In the contemporary digital era, consumers exhibit evolving preferences, which are influenced by the rapid advancements in new technologies (Song, 2021). To understand and cater to these customers, businesses collect vast amounts of customer data from various sources, such as

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social media, server logs, web click streams, mobile apps and databases. However, the value of this data lies in the tools that can process and analyse it (Rana *et al.*, 2021). For instance, machine-learning algorithms can optimize prospect scoring by identifying prospects who share similar traits with existing customers, enabling salespeople to prioritize their actions towards the most promising sales opportunities (Sawal *et al.*, 2022).

Data Analytics Capabilities (DAC) have emerged for Customer Relationship Management (CRM) systems to balance with other Critical Success Factors (CSFs), mainly identified as people, process and technology (Chapman, 2019; Mikalef & Krogstie, 2020; Shahbaz *et al.*, 2020; Akter *et al.*, 2020; Song & Liang, 2021; Jabado & Jallouli, 2021). DAC allow businesses to gain a deeper understanding of their customers, make better decisions, enhance the customer experience, predict customer behaviour, increase efficiency, prevent data fragmentation, and implement data-driven marketing and sales strategies (Rana *et al.*, 2021; Chatterjee *et al.*, 2022). These capabilities enable businesses to optimize their CRM strategies to form responses to real-time shifts in customers' actions and behaviour (Mahafzah *et al.*, 2020; Maulana & Nalitupulu, 2022), thus improving their overall competitive performance (Chapman, 2019; Mahafzah *et al.*, 2020; Maulana & Nalitupulu, 2022).

Despite the growth in data quantity, speed, and diversity, there is a gap in empirical research about how DAC translates into competitive performance (Maulana & Nalitupulu, 2022). Furthermore, research on effective integration of DAC in operations and necessary organizational capabilities is limited (Kaabi & Jallouli, 2019; Jallouli & Kaabi, 2022). There is a recognized need for more empirical evidence to substantiate the impact of DAC initiatives on business value (Mikhalef *et al.*, 2020). The debate continues in academic and business circles about the conditions under which big data analytics can enhance business profitability (Mikhalef *et al.*, 2020).

Recently, a systematic literature review (SLR) conducted by Jabado & Jallouli (2023) highlighted the transversal role of DAC with other CSFs for CRM systems (technology, people, and process), along with its impact on firms' intrinsic outcomes (marketing decisions) and extrinsic outcomes (net benefits). The SLR results provided, for each dimension, the retained variables, measurement scales and items. It also argues that the integration of DAC as a CSF strengthens the impact of all CSFs (technology, people, process, DAC) on firms' intrinsic (marketing decisions and customer satisfaction) and extrinsic outcomes (firms' profitability presented by net benefits for firms and customers). These findings are supported by theoretical grounding, yet highlight a gap in empirical evidence.

The purpose of this paper is two-fold: (1) to present the conceptual foundation of the impact of DAC for CRM systems on marketing decisions and business profitability; and (2)

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empirically to estimate the impact of integrating DAC on marketing performance and business profitability. Indeed, this study aims to answer the following question: To which extent do CRM systems, integrating DAC, impact marketing decisions and business profitability? The proposed framework will be empirically tested in the context of the retail industry.

The first part of the study will provide a brief theoretical background about CRM systems and DAC, along with the research hypotheses for successful CRM implementation. The second part will discuss the quantitative method adopted to estimate the impact of DAC on CRM effectiveness and business profitability. The third part will present the data analysis with the results, followed by the discussion, while emphasising the implications of the research. The last part will conclude this study and describe its limitations, with recommendations for future research.

Theoretical Background and Research Hypotheses

The following section will provide a brief literature review about the theoretical framework guiding the study, along with the relevant research hypotheses to be tested.

CRM Critical Success Factors (CSFs)

Pan *et al.* (2007) describe CRM 'success factors' as the fundamental elements necessary for any CRM implementation to succeed. Critical Success Factors (CSFs) are identified as the key elements influencing an organization's achievement: Indeed, Guerola-Navarro *et al.* (2020) conceptualize CRM as comprising three core components: sales, marketing, and services, highlighting the importance of a customer-focused strategy in contemporary marketing practices.

People, process, technology framework

Originating in the 1970s for salesforce automation, CRM integrates people, processes, and technology (PPT) to manage relationships, focusing on customer retention and relationship development (Alnofeli *et al.*, 2023). In the PPT framework, maintaining balance among components is important: any imbalance compromises its effectiveness (Dąbrowska *et al.*, 2022; Biagi, Patriarca & Di Gravio, 2021). Thus, skilled people and well-designed processes are essential, alongside advanced technology (Biagi, Patriarca & Di Gravio, 2021). However, with growing technological influence, the framework's relevance is challenged (Davenport *et al.*, 2020). Wang & Dong (2022) suggest that integrating "data" might redefine and enhance its success parameters. Indeed, several studies attempted to investigate how DAC have become essential as a critical success factor for processing the vast amount of data collected from CRM systems, in addition to the PPT framework (Chapman, 2019; Jabado & Jallouli, 2021; 2023; Mikalef & Krogstie, 2020; Shahbaz *et al.*, 2020; Akter *et al.*, 2020; Song & Liang, 2021):

Technology dimension - Integration of ERP system with CRM functionality

Previous studies highlighted the importance of unified data platforms, by integrating the Enterprise Resource Planning (ERP) system with CRM functionality, such as the omni-channels and suppliers' portals (Chen *et al.*, 2018; 2020). It provides organizations with the necessary tools to stay competitive in today's market. By leveraging the insights gained from this integration, businesses can improve their intrinsic outcomes (marketing decisions) such as customer satisfaction, better track their customer relationships, and optimize their operations (Kitchens *et al.*, 2018). Therefore, the following hypothesis will be tested:

H1: Technology – 'Integration of ERP system with CRM functionality' has a positive impact on Intrinsic Outcomes – 'Effective Marketing Decisions & Customer Satisfaction'.

People dimension – internal commitment: 'human skills'

The success of CRM depends not only on the use of technology but also on the internal commitment of employees (human skills) to customer satisfaction and involvement in marketing decisions through customer relationship management: Hamida *et al.* (2022) emphasize the importance of employee commitment and buy-in for successful CRM implementation. Employee commitment allows them to take ownership of customer interactions and provide high-quality customer service. This can be fostered by providing training and development opportunities, creating a culture of customer service, and recognizing and rewarding employee contributions to CRM (Shahbaz *et al.*, 2020). As such, the following hypothesis will be tested:

H2: People – 'Human Skills' have a positive impact on Intrinsic Outcomes – 'Effective Marketing Decisions & Customer Satisfaction'.

Process dimension – 'Process holistic approach and marketing channel strategies'

Successful implementation of CRM requires more than just the adoption of technology; it also involves focusing on underlying processes and organizational structures, focusing mainly on a process holistic approach and on marketing channel strategies for traditional stores and online shopping. This would ensure improved intrinsic outcomes (marketing decisions and better customer satisfaction) (Aljawarneh *et al.*, 2020; Kaabi & Jalouli, 2019; Rund, 2018). Thus, the following is hypothesized:

H3: Process – 'Process Holistic Approach and Effective Marketing Strategies' has a positive impact on Intrinsic Outcomes – 'Effective Marketing Decisions & Customer Satisfaction'.

Data analytics capabilities dimension

Gupta & Chandra (2020) describe DAC as the process of converting the extensive data produced by CRM systems into impactful marketing strategies, thereby enhancing the overall performance of businesses. They can facilitate predictive modelling, forecasting, and the identification of potential cross-selling or upselling opportunities. Furthermore, DAC can be divided into three interconnected domains aimed at improving customer experience, decision-making, and overall strategy ("Real-Time Analytics", 2018): proactive analytics, which involves the use of AI to integrate customer awareness and marketing efforts (De Mauro *et al.*, 2022); contextual analytics, which focuses on leveraging real time insights from customer interactions to refine marketing approaches (Akter *et al.*, 2020); and the ability to unify customer data platforms across both online and physical stores ("Real-Time Analytics", 2018).

Intrinsic outcomes dimension – 'Customer satisfaction and effective marketing strategies'

Leveraging new technologies along with DAC empower companies to enhance customer experiences, make informed decisions, and drive business success in the context of CRM (Praful Bharadiya, 2023). Such capabilities foster personalized marketing, boosting customer satisfaction and loyalty (Chen *et al.*, 2020). Data analytics also spotlight customer trends, aiding targeted marketing strategies (Praful Bharadiya, 2023). By analysing CRM data, companies obtain strategic insights that refine marketing decisions and customer satisfaction, and can pinpoint growth opportunities (Mahafzah *et al.*, 2020; Maulana & Nalitupulu, 2022). As such, when DAC is included as a CSF for CRM systems, the following hypothesis will be tested to assess the impact on firms' intrinsic outcomes:

H4: 'Data Analytics Capabilities' has a positive impact on Intrinsic Outcomes – 'Effective Marketing Decisions & Customer Satisfaction'.

Extrinsic outcomes' dimension – business profitability 'net benefits'

CRM efficiency is optimized (firms' net benefits) only when data is centralized in one system and CRM features are accessible to all relevant stakeholders in the company (Maulana & Nalitupulu, 2022). For example, CRM solutions will involve front- and back-of-house departments, IT support, suppliers' portals, call centres, sales, marketing and commercial teams; they would be all unified through a centralized information system for effective decision-making and an increase in customer retention in traditional stores and online, leading to a boost in a firms' profitability (Dixit, 2022). As such, the following is hypothesized:

H5: Technology – 'Integration of ERP system with CRM functionality' has a positive impact on Extrinsic Outcomes – 'Net Benefits'.

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Berg *et al.* (2023) emphasize the importance of employees' involvement in how digital technologies are used and deployed. This involvement suggests that human skills, particularly in decision-making and technology application, are essential for optimizing the use of technology in the workplace. Furthermore, the advocacy for a human-centred design in technology implies a recognition of the value of human skills in shaping technology to meet human needs, rather than allowing technology dictate outcomes. This approach can lead to more effective and beneficial use of technology, impacting business profitability.

In contrast, Parker & Grote (2020) point out that heavy reliance on digital technologies, such as Knowledge Management Systems (KMSs), reduces the need for interpersonal knowledge-sharing and social interaction among colleagues. This diminished human interaction can lead to a more alienated workforce. This can negatively affect employee engagement and satisfaction. Disengaged employees are typically less productive and less innovative, which can adversely impact overall business profitability and performance. Based on previous literature, the following hypothesis will be tested:

H6: People – 'Human Skills' has a positive impact on Extrinsic Outcomes – 'Net Benefits'.

Hsu *et al.* (2021) emphasize the efficiency of CRM processes when they align with a company's strategic objectives, including customization and efficient data management. Effective CRM systems should streamline business procedures, support new product development, and enhance management capabilities. A customer-centric approach is critical for improving interdepartmental collaboration and data exchange, thus boosting customer relationship efficiency (Hargreaves *et al.*, 2018; Rahimi, 2022). Presently, businesses face challenges in customer analytics capabilities due to the complexity of data extracted from e-commerce platforms. A key challenge is creating a reliable, comprehensive data architecture for processing consumer insights, which is essential for shaping future marketing strategies, both online and in-store ("Real-Time Analytics", 2018). Barusman & Habiburrahman (2022) highlight the necessity of a holistic process that fosters collaboration among stakeholders, thereby enhancing the role of CRM systems in linking information technology with business profitability. As such, the following will be hypothesized:

H7: Process – 'Process Holistic Approach and Effective Marketing Strategies' has a positive impact on Extrinsic Outcomes – 'Net Benefits'.

As discussed in previous literature, integrating DAC into CRM systems is recognized as a key approach for achieving significant business outcomes (Gupta & Chandra, 2020). This multifaceted approach includes ("Real-Time Analytics", 2018): aligning CRM with a company's strategic objectives; enhancing business process efficiency; and improving sales performance. Adopting a customer-centric approach through data-driven insights enhances customer relationships and satisfaction, thereby positively influencing business outcomes. Additionally, a holistic and collaborative integration of data analytics in CRM ensures seamless alignment with business strategies, contributing to increased profitability and operational efficiency (Akter *et al.*, 2020). The combination of these factors leads to enhanced operational efficiency, greater customer satisfaction, and ultimately, improved business profitability (Chapman, 2019; Mahafzah *et al.*, 2020; Maulana & Nalitupulu, 2022). As such, the following hypothesis will be tested:

H8: 'Data Analytics Capabilities' has a positive impact on Extrinsic Outcomes – 'Net Benefits'.

Previous studies explored CRM benefits, highlighting its ability to improve both firm performance (marketing decisions) and customer satisfaction. Perceived sales performance and competitive performance were identified as two critical components in understanding the net benefits of CRM (Chatterjee *et al.*, 2022). Specifically, Sawal *et al.* (2022) confirmed that perceived sales performance leads to higher levels of customer satisfaction, which translates into improved competitive advantage. As such, the following is hypothesized:

H9: Intrinsic Outcomes – 'Effective Marketing Decisions & Customer Satisfaction' has a positive impact on Extrinsic Outcomes – 'Net Benefits'.

Research model

The model guiding this study is presented in Figure 1.

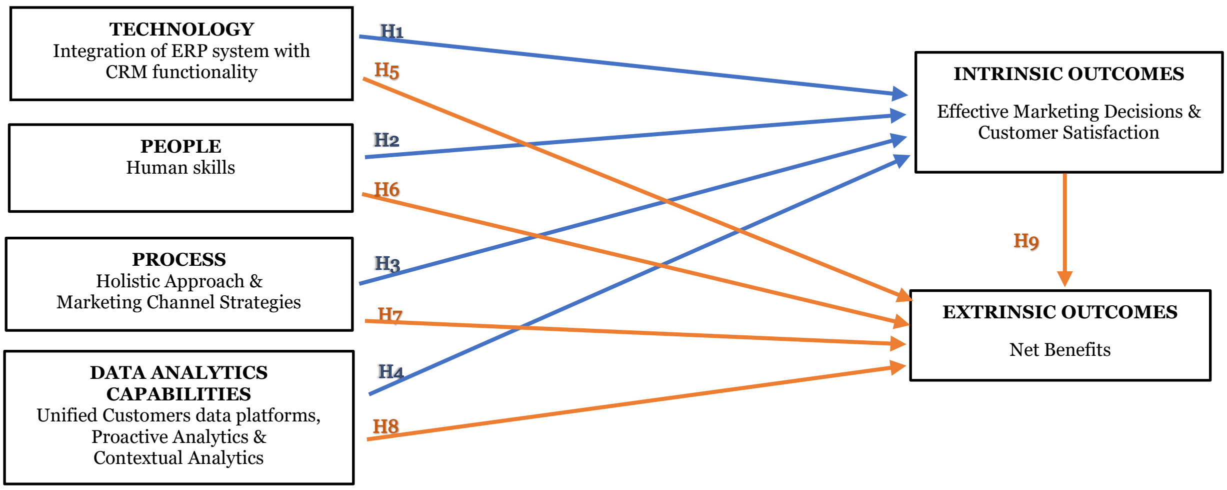

Figure 1. Research Model of the impact of Technology, People, Process and Data Analytics Capabilities on Effective Marketing Decisions, Customer Satisfaction and Net Benefits

Figure 1 synthesizes all dimensions of CSFs for CRM successful implementation. The general structure of the framework allows the analysis of: (1) the first level that involves the critical success factors of CRM systems by the independent variables of Technology, People, Process and DAC; (2) the second level, which examines Intrinsic Outcomes through the mediating variables 'Effective Marketing Decisions and Customer Satisfaction'; and (3) the last level, which measures the Business Profitability by the dependent variable 'Net Benefits'.

Methodology

This section outlines the methodology used to answer the research question: 'To which extent can CRM systems, integrating DAC, impact marketing decisions and business profitability?' Through the SPSS statistical tool, several statistical analyses were conducted on the data collected from the surveys.

Sample design and data collection

The study's target population comprised 131 employees who were primary users of the ERP system at 42 retail branches in Lebanon. The choice of this population, although considered small, is significant: indeed, the integration of the CRM system with the existing ERP is at its early stages in most branches, providing a ripe context for the research. Thus, the 131 employees constituted the only target population available that could serve as respondents in this study.

A questionnaire-based survey was utilized for primary data collection and testing the research model, using a 5-point multidimensional Likert-type scale. It contained questions based on Jabado & Jallouli's (2023) SLR findings, covering the six dimensions of the research model — Technology, People, Process, DAC, Intrinsic and Extrinsic Outcomes — along with the relevant measurement scales. Created with Google Forms, the questionnaire link was distributed to all 131 ERP-CRM users.

Data collection started on June 1, 2021, and ended on August 31, 2021. All 131 responses were valid. Respondents provided demographic information about their gender, age, education, company position, and ERP system usage, along with their answers to the variable-based questions.

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was used to explore the underlying structure of the CSF dimensions in CRM implementation, including Technology, People, Process, and DAC (Hair *et al.*, 2010). The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) values for all dimensions exceeded the acceptable threshold of 0.6 (Brown, 2006), with an overall KMO = 0.749 (Table 1), indicating that data is suitable for factor analysis. Bartlett's Test of Sphericity (Table 1) showed a significant Chi-Squared value of 15300.799 (df = 4278, Sig. = 0.000), indicating that the variables are also correlated and suitable for a factor analysis (Brown, 2006).

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Table 1. KMO and Bartlett's Test

Factor Analysis Dimension	KMO MSA	Bartlett's Test of Sphericity		
		Approx. Chi-Squared (χ^2)	df	Sig.
All Dimensions of CSFs (Technology, People, Process, DAC)	0.749	15300.799	4278	0.000
Technology	0.856	871.167	45	0.000
People	0.857	1052.945	66	0.000
Process	0.922	2986.349	276	0.000
Data Analytics Capabilities	0.893	4112.671	666	0.000

The Principal Component Analysis (PCA) further reveals that the cumulative variance explained is 80%. These results indicate a strong representation of the data structure of the critical success factors through the extracted components: Technology, People, Process, and DAC (Hair *et al.*, 2010). The next step involves applying various reliability and validity tests to verify the factor structure previously identified.

Table 2. Summary of Reliability and Validity Indicators

Dimension	Sub-Dimension	*Measurement Scale*	Code	# of Items	Cronbach Alpha	Range of Inter-Item Correlations	AVE
Whole Questionnaire					**0.989**		
6	**11**	***24***		**121**			
Technology		***2***	**TECH**	**10**	**0.907**		
	Integration of ERP system with CRM functionality	*System Quality*	SQ	5	0.968	0.895** to 0.927**	0.738
		Knowledge Stock	KS	5	0.893	0.721** to 0.941**	0.659
People		***3***	**PEO**	**12**	**0.926**		
	Internal Commitment (Human Skills)	*Customer Interaction Mgmt Capability*	CIMC	5	0.918	0.703** to 0.934**	0.756
		Customer Orientation	CO	4	0.866	0.700** to 0.914**	0.705
		Customers' Involvement	CI	3	0.905	0.858** to 0.930**	0.767
Process		***5***	**PRO**	**24**	**0.97**		
	Process Holistic Approach	*Organizational Structure*	OS	3	0.84	0.846** to 0.886**	0.71
		Customer-Centric Organizational System	CCOS	5	0.876	0.723** to 0.934**	0.625
		Sales Automation	SA	6	0.943	0.815** to 0.950**	0.773
	Marketing Channel Strategies	*Marketing Channel Strategies*	MCS	5	0.895	0.796** to 0.871**	0.733
		Marketing Automation	MA	5	0.955	0.880** to 0.932**	0.827
Data Analytics Capabilities		***7***	**DAC**	**37**	**0.966**		
	Unified Customer Data platforms	*Knowledge Mgmt Systems*	KMS	4	0.894	0.794** to 0.932**	0.67
		Advanced Analytics	AA	4	0.877	0.797** to 0.913**	0.693
		IT Capability	IC	4	0.89	0.756** to 0.848**	0.697
	Proactive Analytics Capabilities	*Big DAC (Human Skills & Intangible)*	BDAC-HI	10	0.929	0.635** to 0.873**	0.534
		Improved Relation Knowledge	IRK	3	0.923	0.902** to 0.956**	0.842
	Contextual Analytics	*Big DAC (Data & Technology)*	BDAC-DT	8	0.925	0.722** to 0.843**	0.691
		Customer Relationship Upgrading Capabilities	CRUC	4	0.893	0.818** to 0.920**	0.811
Intrinsic Outcomes		***5***	**IO**	**25**	**0.955**		
	Effective Marketing Decisions	*Marketing Capabilities*	MC	4	0.851	0.708** to 0.903**	0.822
		Dynamic Capabilities	DC	9	0.91	0.571** to 0.879**	0.683
		Better Customer Services (Perceived)	BCSP	4	0.873	0.757** to 0.886**	0.807
		Personalization	PER	3	0.928	0.889** to 0.945**	0.837
	Customer Satisfaction	*Customer Satisfaction & Loyalty*	CSL	5	0.931	0.772** to 0.945**	0.812
Extrinsic Outcomes		***2***	**NB**	**13**	**0.946**		
	Net Benefits	*Perceived Sales Performance*	PSP	3	0.94	0.896** to 0.934**	0.792
	Business Profitability	*Competitive Performance*	CP	10	0.936	0.668** to 0.953**	0.661

** sig. at $p<0.05$

Reliability and validity analysis

Table 2 provides a summary of the research model's structure, along with the relevant reliability and validity indicators. Cronbach's alpha values range from .851 to .989 across all dimensions and exceed the recommended threshold of 0.7 (Hair, 2010), thus indicating that the items have relatively high internal consistency. Typically, for a scale to be considered reliable, the inter-item correlation should range between 0.2 to 0.8 (Hair, 2010). Table 2 indicates that the ranges of inter-item correlations meet this criterion, indicating good reliability.

Convergent validity was also assessed through Average Variance Extracted (AVE): the lowest value being 0.534 for DAC (Human Skills and Intangible), and the highest being 0.842 for DAC (Improved Relation Knowledge). Moreover, all values exceed the acceptable threshold of 0.5 (Cohen, 1988), meaning that a significant proportion of variance in the items is captured by the factor. Additionally, the square root of AVE (√AVE) is greater than the inter-construct correlations, supporting discriminant validity (Hair, 2010).

Regression analysis

The Multiple Linear Regression (MLR) analysis aimed at examining the impact of CSFs for CRM systems on Intrinsic Outcomes (Effective Marketing Decisions and Customer Satisfaction). This section will provide the statistical tests that were used to check the assumptions of the regression analysis.

Normality tests (Appendix), including Kolmogorov-Smirnov and Shapiro-Wilk, were performed, yielding p-values greater than 0.05 for most dimensions, suggesting that the assumption of normality was not violated (Razali & Wah, 2011). Skewness and kurtosis results fell within the acceptable range of -2 to +2, indicating no significant deviation from normality. Additionally, histograms and Q-Q plots complemented the normality analysis by providing a visual validation of the data distribution for each dimension.

The Variance Inflation Factor (VIF) was used to assess multicollinearity among predictors (Tables 3 to 5), with all VIF values below the threshold of 10 (Vittinghoff *et al.*, 2012), suggesting that collinearity was not a concern.

Additionally, the linearity between the independent variables (Technology, People, Process, DAC) and the dependent variables (Intrinsic Outcomes & Net Benefits) was tested. Results confirmed a significant linearity between all independent variables and dependent ones.

Next, a regression analysis will be conducted to determine the directionality and causality of these relationships.

Findings: Hypotheses Testing

Results for H1 though H4 are summarized in Table 3: Process (H2), DAC (H3) and People (H4) significantly predicted intrinsic outcomes ($F= 159.667$, $p < .001$), but Technology did not

(β = -0.010, t = -0.140, p = 0.890). One potential rationale could be that the integration of the ERP system in the studied stores is still in the preliminary stages, and it often takes time before the outcomes are evident and discernible. Indeed, employees might not immediately notice improvements in operational efficiency, data accessibility, or workflow automation that the ERP system results in (Sawal *et al.*, 2022). The overall results were statistically significant, explaining 79% (R^2 = .790) of the variance in Intrinsic Outcomes (Effective Marketing Decisions and Customer Satisfaction).

Table 3. Summary of Multi Linear Regression (H1 to H4): Outcome IO

Hypothesis	Independent Variable (Predictor)	R	R^2	F	Sig (F)	Beta (β)	t	Sig (t)	(VIF)	Status
H1 (TECH => IO)	**TECH**	-	-	-	-	-0.010	-0.140	0.890	-	Not Supported
H2 (PRO => IO)	**PRO**	0.889	0.790	159.667	0.000	0.504	6.120	0.000	3.951	Supported
H3 (DAC => IO)	**DAC**					0.333	3.114	0.000	5.420	Supported
H4 (PEO => IO)	**PEO**					0.163	2.144	0.034	3.074	Supported

Stepwise Method / df (Regression)=3, df (Residual) = 127, N = 130

The MLR analysis then assessed the prediction of Net Benefits for the Firm and Customers (Profitability) through Technology, People, Process, and DAC. Results for H5 though H8 are summarized in Table 4.

Table 4. Summary of Multi-Linear Regression (H5 to H8): Outcome NB

Hypothesis	Independent Variable (Predictor)	R	R^2	F	Sig (F)	Beta (β)	t	Sig (t)	(VIF)	Status
H5 (TECH => NB)	**TECH**	-	-	-	-	-0.080	-0.935	0.352	-	Not Supported
H6 (PEO => NB)	**PEO**	-	-	-	-	0.334	0.295	0.769	-	Not Supported
H7 (PRO => NB)	**PRO**	0.851	0.724	167.841	0.000	0.493	4.987	0.000	3.896	Supported
H8 (DAC => NB)	**DAC**					0.508	4.632	0.000	3.896	Supported

Stepwise Method / df (Regression)=2, df (Residual) = 128, N = 130

Process (H7) and DAC (H8) were significant predictors of Net Benefits (F = 167.841, p < .001), with Technology (H5: β = -0.080, t = -0.935, p = 0.352) and People (H6: β = 0.334, t= 0.295, p = 0.769) showing no effect. Overall, results are significant, explaining 72.4% (R^2 = .724) of the variance in Net Benefits. Furthermore, a simple linear regression analysis assessed the prediction of Net Benefits for the Firm and Customers (Profitability) through Intrinsic Outcomes (Effective Marketing Decisions & Customer Satisfaction). Table 5 reports the findings of testing hypothesis (H9).

Table 5. Summary of Simple Linear Regression (H9): Outcome NB

Hypothesis	Independent Variables (Predictor)	R	R^2	F	Sig (F)	Beta (β)	t	Sig (t)	(VIF)	Status
H9 (IO => NB)	**IO**	0.888	0.788	480.205	0.000	0.939	21.914	0.000	1.000	Supported

Stepwise Method / df (Regression)=1, df (Residual) = 129, N = 130

Results are statistically significant ($F = 480.205$, $p < .001$), indicating that Intrinsic Effective Marketing Decisions and Customer Satisfaction are a strong predictor of a firms' Business Profitability.

Overall, MLR results are highly significant with large F values and non-significant results for Technology, suggesting that, while Technology is an important factor, it may not directly influence outcomes as strongly as Process and DAC. These results provide answers to the research objectives and questions; they suggest that 'Process' and 'DAC' are critical factors contributing to both "Marketing Decisions and Customer Satisfaction" and "Net Benefits", highlighting the importance of efficient processes and data analytics in achieving organizational goals. Conversely, the integration of ERP with CRM technology, while essential, may not directly predict these outcomes. These results emphasize the importance of DAC's integration, along with "Human Skills" and "Process Holistic Approach", in enhancing CRM systems' effectiveness and boosting profitability. Technology as defined in this model does not appear to have a significant direct effect, nor do human skills alone. However, when these are combined with process and DAC strategies, they may still contribute to overall outcomes.

Discussion and Implications

This study highlights the critical role of DAC in CRM systems within the retail industry. This emphasizes the growing significance of DAC in conjunction with Technology, People, and Process, in line with the trend towards data-driven decision-making in retail (Mahafzah *et al.*, 2020; Maulana & Nalitupulu, 2022). The findings underscore the necessity for retail industries to develop solid analytics capabilities to maintain competitiveness (Chapman, 2019; Jabado & Jallouli, 2021; 2023; Mikalef & Krogstie, 2020; Shahbaz *et al.*, 2020; Akter *et al.*, 2020; Song & Liang, 2021) . The study also reveals the importance of harmonizing Technology, People, Process and DAC in CRM systems. The results suggest that successful CRM systems should encompass a combination of advanced technological tools, skilled personnel, and well-designed processes (Dąbrowska *et al.*, 2022; Biagi, Patriarca & Di Gravio, 2021) in addition to DAC (Kaabi & Jallouli, 2019).

Interestingly, MLR results indicate that technology, specifically CRM-ERP integration, does not significantly impact intrinsic and extrinsic outcomes. This finding suggests a potential underutilization or immature integration of technology in the sample studied, highlighting a gap between technological capability and its effective application (De Mauro *et al.*, 2022). This calls for an improved alignment between technological infrastructure and business strategies (Chen *et al.*, 2018; 2020). Furthermore, the study finds that Process positively influences both intrinsic outcomes and net benefits, highlighting the importance of holistic approaches and effective marketing strategies in CRM (Aljawarneh *et al.*, 2020). This indicates the need for an integrated CRM approach that combines various customer needs.

The significant positive impact of DAC on both intrinsic and extrinsic outcomes reinforces its important role in enhancing marketing decisions, customer satisfaction, and profitability. This aligns with the increasing trend of data-driven decision-making in the retail industry (Praful Bharadiya, 2023;). Moreover, there is an emphasis on the complex role of human skills in CRM systems, where People's impact is significant on marketing decisions and customer satisfaction, but not on net benefits. This suggests that, while employee capabilities and internal commitment are essential (Hamida *et al.*, 2022), their direct financial contributions may be moderated by several factors, to be further examined (Berg *et al.*, 2023; Biagi, Patriarca & Di Gravio, 2021).

On a theoretical level, the findings contribute to the existing literature by empirically validating the integration of DAC as a CSF in CRM systems, a relatively underexplored area in existing research. This shifts the traditional focus from technology-centric factors to a more balanced view that considers the interplay of technology with processes, people, and data analytics. This adds a new dimension to the theoretical understanding of CRM success factors, emphasizing the role of Data Analytics Capabilities in addition to the traditional factors of Technology, People, and Process. The study also broadens the scope of CRM implementation theory by focusing on the interplay between Process, DAC, and People, moving beyond Technology. This comprehensive approach provides new insights, especially in retail, and proposes a more balanced CRM model integrating technological, analytical, human, and process elements.

On a managerial level, and to the best of our knowledge, it is the first study that provides empirical evidence in the retail industry, through a quantitative study, of the positive effect of DAC and Process as CSFs for CRM systems on Net Benefits. Subsequently, results have important practical implications for businesses seeking to improve their profitability through the adoption of CRM strategies. The research also emphasizes the need for organizations in the retail industry to carefully balance the implementation of CRM systems: managers should prioritize process optimization, employee training, and DAC over solely focusing on technological integration of CRM systems. A holistic approach can lead to more effective marketing decisions and enhanced customer satisfaction to maximize net benefits.

Overall, the study emphasizes the multifaceted nature of CRM systems and the synergistic interplay between Technology, People, Process, and DAC. This comprehensive approach is essential in the retail sector to maximize the benefits of CRM systems, emphasizing the need for continuous training and development in the CRM domain (Kumar & Mokha, 2021) to enhance overall customer satisfaction and profitability for practitioners in the retail industry looking to optimize their CRM strategies (Akter *et al.*, 2020).

Conclusions, Limitations and Recommendations

CRM systems have been widely adopted by organizations as a means of improving customer satisfaction and loyalty, and, ultimately, business performance. Previous literature has established that the dimensions of People, Process and Technology (PPT) are CSFs for CRM systems. Additionally, the literature review indicates that DAC has also been identified as a CSF for CRM systems in previous studies (Chapman, 2019; Mikalef & Krogstie, 2020; Shahbaz *et al.*, 2020; Akter *et al.*, 2020; Song & Liang, 2021). This research has provided, through a survey in the context of retail industry, empirical estimations of the impact of DAC, People, Process and Technology as critical factors for successful CRM implementation.

This study is, to the best of our knowledge, the first of its kind to investigate the role of DAC as a CSF for CRM systems. To answer the research question and test the research hypotheses, an EFA was conducted to test the inclusion of DAC in the CSFs framework for successful CRM implementation (Wang & Dong, 2022). As well, the results of the MLR have provided empirical evidence for the importance of DAC as a CSF for CRM systems, in addition to the three dimensions largely accepted in the PPT framework. Furthermore, this research has confirmed that, when DAC and a process holistic approach are integrated together as CSFs of CRM systems, they have a significant positive impact on effective marketing decisions, customer satisfaction and profitability in the retail industry. The role of people and technology is yet to be examined further to assess the type of interaction they hold with other dimensions.

The study's geographical and industry-specific limitations are acknowledged. Its cross-sectional nature also overlooks temporal changes, especially in early ERP-CRM integration phases. Future research should: (1) explore case studies in diverse sectors with CRM and ERP integration to understand the benefits and challenges; (2) assess DAC and ERP-CRM integration effects across industries; (3) examine how CSFs collectively influence CRM efficiency; (4) look at customer perspectives on CRM outcomes; (5) conduct longitudinal research on the shifting impact of CSFs on CRM; (6) investigate how human skills and technological integration enhance CRM systems; and (7) analyse the roles of Technology and People on CRM profitability and benefits amid technological and analytical advancements.

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Appendix

Table A1. Summary: Descriptive Statistics for Normality Tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
TECH	0.129	30	0.200*	0.956	30	0.241
PEO	0.135	30	0.172	0.950	30	0.164
PRO	0.162	30	0.044	0.947	30	0.141
DAC	0.127	30	0.200*	0.945	30	0.123
IC	0.150	30	0.081	0.941	30	0.098
NB	0.213	30	0.001	0.931	30	0.051

* This is a lower bound of the true significance.
a. Lilliefors Significance Correction

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Enhancing IoT Security: Proactive Phishing Website Detection Using Deep Neural Networks

Case study: Smart Home

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Abstract: The Internet of Things (IoT) has proven its utility across various domains, including healthcare, agriculture, industry, and finance. It comprises Internet-connected devices that offer remote control capabilities. However, this very connectivity exposes these devices to potential cyberattacks. Cybercriminals can exploit the vulnerabilities in these devices by sending deceptive emails or text messages containing malicious links leading to hacker websites or destructive applications. This allows them unauthorized access to connected devices and the acquisition of sensitive personal information. Such malicious tactics are collectively known as phishing and pose one of the most prevalent threats.

This article presents an innovative method that harnesses the power of a Deep Neural Network to accurately classify and proactively prevent phishing websites by analyzing their URLs. The method is demonstrated through a smart home use case, aiming to reinforce IoT security and safeguard users' sensitive data by proactively identifying and preventing phishing attacks. By harnessing the power of the Deep Learning model, this innovative technique seeks to enhance online safety and protect users from potential cyber threats.

Keywords: Smart Home, Phishing, URL Classification, Security, Deep Neural Network.

Introduction

IoT, short for the Internet of Things, encompasses a network of interconnected devices and appliances that are connected to the Internet. This technology has had a profound impact on our daily lives, enhancing the capabilities of machines to handle demanding tasks, addressing monotonous activities, and enriching our quality of life by providing healthier, more productive, and comfortable experiences.

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However, this connectivity also exposes us to cybercrime attacks, with one of the most common being phishing attacks. These attacks typically involve tricking users through emails or text messages, leading them to visit seemingly legitimate websites and click on malicious links. As a result, cybercriminals can exploit this technique to collect personal, intimate, confidential, and sensitive information (Abbas *et al.*, 2021; Atitallah *et al.*, 2020; Safi & Singh, 2023).

Phishing attacks pose a significant threat to IoT devices, often leading to data breaches. To mitigate these risks, it is essential to establish a strong security mechanism that can identify potential threats, vulnerabilities, and countermeasures to prevent phishing attacks on IoT devices (Abbas *et al.*, 2021; Atitallah *et al.*, 2020).

This work delves into the endeavours of researchers to improve the cybersecurity of IoT systems and the diverse models suggested for countering phishing attacks. Specifically, we will focus on detecting and preventing phishing attempts in smart homes, which are considered an integral part of the IoT ecosystem. As a part of our research, we will introduce our proposed model based on Deep Neural Networks (DNNs).

The paper presentation will follow a structured format comprising various sections. The Literature Review will provide an overview of the addressed problem and introduce key concepts related to smart homes, exploring existing literature on detecting phishing attacks in the IoT. The Vocabulary and Methods section will outline the terminology and methodologies employed. The Methodology and Experience section will detail the steps taken to develop the proposed model. Results and Discussion will focus on presenting and analyzing research findings, discussing their implications and potential applications. The Comparative Analysis section will compare results with other learning models. Finally, the Conclusion and Future Work section will succinctly summarize key findings, highlight their implications, and propose potential avenues for future research to advance the field.

Literature Review

IoT is a groundbreaking technology facilitating seamless connections between objects and the Internet, reshaping how we interact with our surroundings. Intelligent devices within this framework collect and transmit data through IoT applications, subject to analysis using advanced artificial intelligence techniques. This empowers the IoT system to make informed decisions, which are then conveyed back to devices for intelligent responses through automated actions. Users can easily manage and control these IoT devices through user-friendly graphical interfaces. Various IoT systems exist, such as smart cars, smart homes, smart cities, and smart buildings. This paper specifically focuses on highlighting the smart home as a prominent example of IoT application (Abbas *et al.*, 2021).

Smart home technologies

A smart home is characterized by the presence of a communication network that connects various electronic products or services, enabling remote control or monitoring. Various objects contribute to this system, including light bulbs, blinds, outlets, thermostats, and TVs. Even refrigerators and vacuum cleaners can be integrated into this ecosystem.

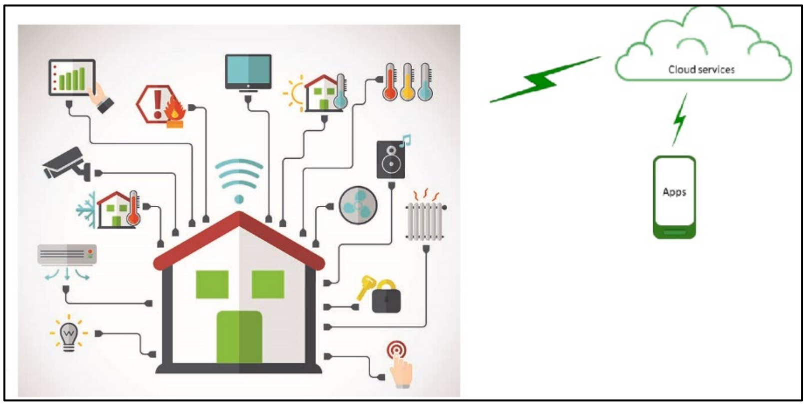

Figure 1. Smart Home

The smart home can be divided into three key areas: devices, cloud services, and consumer. In the devices sector, diverse smart devices are interconnected to establish the fundamental framework of the smart home ecosystem. The cloud services zone acts as a centralized hub facilitating communication and data exchange between these devices and cloud-based services, enhancing functionality and accessibility. Finally, the consumer zone serves as the interface where end-users interact with and manage their smart home system, providing a seamless and personalized experience. This tripartite division allows for a clear delineation of the essential components and their respective roles within the smart home framework.

Smart home security and risks

A smart home encounters various security threats, with the primary issue being the inadequate protection of individual devices. Some IoT home devices are rushed to market without properly addressing security concerns. User manuals often overlook privacy matters or lack sufficient information to guarantee the safety of the devices. Experts stress the importance of anticipating device breaches rather than dismissing them as unlikely events, as most IoT devices are easily exploited and provide minimal protection.

Furthermore, the integrity of a smart home network may be jeopardized, providing unauthorized individuals with the ability to retrieve stored data. Malevolent actors could observe patterns in device usage to identify periods when the homeowner is absent, posing a significant security risk. Administering a smart home network through the primary Internet account exposes not only data from IoT devices but also places various personal information at risk, such as emails, social media accounts, and even banking details. Among the primary vulnerabilities that can lead to data breaches, phishing remains a significant threat.

In this study, we propose a deep learning (DL)-based model aimed at identifying phishing URLs. This model can be integrated into the smart home system by configuring a proxy at the modem level to utilize the model for redirecting web traffic. The proxy is thus capable of leveraging the phishing detection model to assess URLs before transmitting them to connected devices.

Phishing

Phishing is a cybercrime where malicious actors impersonating legitimate institutions communicate with individuals through telephone, email or text messages. The intention behind these deceptive communications is to deceive individuals into revealing sensitive information, including personally identifiable passwords, credit card and banking authorizations, and data. Once these details are acquired, the perpetrators can access crucial accounts, leading to potential identity theft and financial losses (Abbas *et al.*, 2021; Safi & Singh, 2023).

In the cyber world, phishing attacks have experienced a significant surge over the last few years. As per the Cybermalveillance.gouv.fr platform, the main trends observed in cybermalveillance during 2021 are as follows (Cybermalveillance, n.d.):

- Phishing continues to be the most significant cyber threat faced by individuals and has seen a notable increase (+82%);
- Online account hacking (+58%) and fraudulent activities related to fake technical support (+18%) are also on the rise.

Additionally, according to APWG (Anti-Phishing Working Group) report, during the fourth quarter of 2022, a significant number of 1,350,037 phishing attacks were recorded. Figure1 illustrates a slight increase compared to the previous quarter, which had already been identified as the worst quarter for phishing attacks ever recorded by the APWG (n.d.).

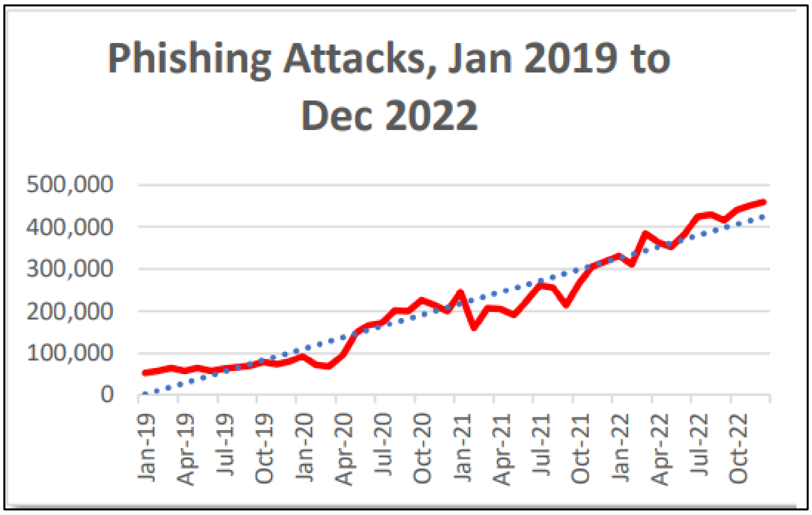

Figure 2. Phishing Attacks, 2019–2022 (APWG, n.d., 4th Quarter 2022)

This work will focus on phishing websites that employ malicious URLs, which are among the most commonly used techniques in phishing attacks. These fraudulent URLs are crafted to trick users into believing they are accessing a reliable website; however, in reality, users unwittingly share their information with cybercriminals.

Phishing website detection

Detecting phishing websites can be challenging due to their deceptive nature. However, several approaches and techniques can help identify them (Barraclough *et al.*, 2013; Berqia & Nacsimento, 2004; Ding *et al.*, 2019; Sahingoz *et al.*, 2019; Yuan *et al.*, 2021):

- **URL Analysis**: Examine the URL for misspellings, extra characters, or variations from the legitimate website. Phishing sites often use URLs that mimic the original domain to deceive users.
- **Webpage Content Analysis**: Analyze the content of the webpage for inconsistencies, poor design, or suspicious elements like fake login forms or requests for personal information.
- **Website Reputation Services**: Utilize reputation services or blacklists that maintain databases of known phishing sites and malicious domains.
- **DNS Monitoring**: Monitor DNS records for changes that may indicate the creation of a phishing site.
- **Detection through Deep Learning or Machine Learning**: Employ deep learning models and machine learning algorithms to analyze features of known phishing sites and create models to detect new ones based on patterns.

Otherwise, numerous literature reviews have been conducted on the topic of phishing detection methods. Researchers have compared various approaches, such as Heuristic, Visual Similarity, Lists Based, Deep Learning models and Machine Learning techniques. The research involves a comprehensive investigation into the algorithms, datasets, and methodologies employed for the detection of phishing websites. Notably, Deep Learning and

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Machine Learning skills are the most prevalent and have demonstrated remarkable accuracy, surpassing 99%, in detecting phishing websites (Bouijij *et al.*, 2022; Liu *et al.*, 2022a; Safi & Singh, 2023; Wei *et al.*, 2020).

Manuel Sánchez-Paniagua and his team focus on anti-phishing techniques utilizing machine learning. They make use of HTML, URL, and web technology features. Their experiments illustrate that by employing a LightGBM classifier alongside a comprehensive set of 54 selected features, phishing websites can be accurately detected with a precision of 97.95%. This evaluation was conducted on the Phishing Index Login Websites Dataset (PILWD) (Sánchez-Paniagua *et al.*, 2022).

Dong-Jie Liu and Guang-Gang Geng introduce three semantic-based phishing detection models leveraging diverse deep learning techniques. These models, namely the Multi-scale In-depth Fusion (MIF) model, Multi-scale Feature-layer Fusion (MFF) model, and Multi-scale Data-layer Fusion (MDF) model, have undergone rigorous testing on a complex dataset, showcasing exceptional recognition capabilities. With an accuracy exceeding 99%, these models demonstrate high effectiveness in detecting phishing attacks (Liu *et al.*, 2022b).

Hamzah Salah and Hiba Zuhair propose a phishing predictive model that that employs a dual deep learning-based architecture, specifically combining Bi-directional Long Short-Term Memory (CNN-BiLSTM) with Convolutional Neural Network. The model utilizes a feature space comprising 60 mutual features from Uniform Resource Locators (URLs). Through experimentation, the model achieves impressive performance with an accuracy of 99.27% (Salah & Zuhair, 2023).

M. A. Adebowale and his team introduce an Adaptive Neuro-Fuzzy Inference System (ANFIS) constructed robust scheme that integrates features from images, text and frames for phishing website detection. By using related features of authentic and non-authentic websites and employing artificial intelligence procedures, this combined approach achieves an impressive accuracy of 98.3% (Adebowale *et al.*, 2019).

Syed Ghazanfar Abbas and his team (Abbas *et al.*, 2021) suggest a threat modelling methodology to classify and mitigate cyber threats that could result in phishing attacks on IoT devices. The study centres around two significant IoT use cases: smart homes and smart autonomous vehicular systems. Applying the STRIDE threat modelling approach, the paper identifies potential threats that have the potential to initiate phishing attacks in both of these use cases.

Sujatha Rajkumar and his team, introduce Deep Learning (DL) techniques, specifically a layered approach called Stacked Long Short-Term Memory (SLSTM), to detect and distinguish between normal and malicious traffic data in real-time IoT environments. The

SLSTM method shows promising results in identifying most IoT attacks and outperforms existing classification methods in terms of real-time detection rates. The approach can be applied to different IoT scenarios, making it valuable for improving the security and reliability of IoT systems (Rajkumar *et al.*, 2023).

Vocabulary and Methods

In this section, we will begin by defining the vocabularies and techniques used to implement our model. Subsequently, we will describe our model in detail.

Deep Neural Network

A Deep Neural Network (DNN) takes inspiration from the neurons in the human brain, which generate outputs in response to external stimuli. Specifically, it is a type of artificial neural network that comprises numerous hidden layers positioned between the input and output layers. Each layer in a DNN contains neurons or nodes that perform mathematical operations on the data they receive. The deeper the network, the more hidden layers it has, and the more complex patterns it can learn. The term "deep" in Deep Neural Networks refers to the multiple layers used to process and learn from the data.

Dense layer

The dense layer, also referred to as the fully connected layer, constitutes a fundamental element in neural networks. Within this layer, every neuron is connected to all neurons in the preceding layer. The dense layer performs matrix-vector multiplication, using the output from the preceding layer as the row vector and the neurons in the dense layer as the column vector. The dense layer assumes a critical role in artificial neural networks, as it is extensively employed and crucial for learning patterns and making predictions grounded on input data.

Dropout

Dropout is a regularization method ordinarily used during the training of neural networks to prevent overfitting (Sabiri *et al.*, 2022). It includes randomly zeroing a portion of input units (neurons) during each update in the training process. This technique prevents the model from overly relying on particular neurons and promotes the learning of more robust features within the network. The decision regarding which neurons to drop out is made randomly during each training iteration. The dropout rate determines the fraction of neurons to be dropped out, typically ranging from 0.2 to 0.5.

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Activation function

The activation function plays a vital role in artificial neural networks by introducing non-linearity. It transforms input data and passes it as output to the next layer, enabling the neural network to learn complex patterns and relationships within the data. Common activation functions like *ReLU* (Rectified Linear Unit), sigmoid, tanh (hyperbolic tangent), and softmax each have unique strengths and weaknesses. The choice of an activation function can greatly impact the neural network's performance across different tasks.

In this work, we use:

- *ReLU* function: it retains the positive input values without altering them, while converting all negative values to zero. Mathematically, *ReLU* is presented as:

$$f(x) = \max(0, x) \tag{1}$$

- *Sigmoid* function: a widely adopted non-linear activation function in artificial neural networks, it maps input values to a range of 0 to 1. This attribute makes it particularly suitable for tasks that entail binary classification and probability predictions. Mathematically, the sigmoid function is presented as:

$$f(x) = \frac{1}{(1+e^{-x})} \tag{2}$$

Dropna

"Dropna" refers to a function used to remove missing or NaN (Not a Number) values from a dataset. It is one of a prevalent data preprocessing procedure in data analysis to handle missing data before feeding it into a model.

In Python, "dropna" is commonly associated with Pandas, a standard library for data analysis and manipulation ("Pandas Tutorial", 2024). Precisely, the "dropna" function is used to drop rows or columns containing missing values from a Pandas DataFrame.

Tokenizer

Tokenization involves the procedure of dividing a given text into reduced segments or tokens. These tokens can encompass various elements, ranging from individual words and characters to subwords. In the Keras tokenizer class (Keras, n.d.), the "*fit_on_texts*" method is employed to update the internal vocabulary based on the texts list provided. It is essential to call this method before utilizing other functions like "*texts_to_sequences*" or "*texts_to_matrix*". This ensures that the tokenizer is properly prepared to handle the text data and perform subsequent tokenization tasks accurately. In this study, we employ the "*texts_to_sequences*" method, which simplifies the transformation of tokens in a text corpus into a sequence of integers.

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Pad sequences

"Pad sequences" is a function frequently used in natural language processing and sequence-modelling tasks to guarantee that all sequences in a dataset have the identical length, by padding or truncating them as needed. The purpose of this function is to guarantee that all sequences in a list have equal lengths. By default, it achieves this by padding each sequence with 0 at the beginning until they all match the length of the longest sequence.

In Python, "*pad_sequences*" is typically part of libraries such as Keras (Keras, n.d.) or TensorFlow (TensorFlow, n.d.), specifically within their sequence or preprocessing modules. It simplifies the data preprocessing step before feeding the sequences into the neural network, as most models require fixed-length input sequences.

Evaluation metrics

In a classification problem, the objective is to allocate samples to particular categories or classes. Various evaluation metrics are employed to gauge the efficiency of a classification model. Here are several commonly utilized evaluation metrics for classification tasks:

Conf_Matrix: presents the model's predictions in a tabular format, comprising four values: TN, FP, FN and TP. This matrix offers a comprehensive overview of how samples were accurately or inaccurately classified for each class.

		Predicted class	
		Class=0 (Benign)	Class=1 (Phishing)
Real class	Class=0 (Benign)	True Positive (TP)	False Negative (FN)
	Class=1 (Phishing)	False Positive (FP)	True Negative (TN)

Figure 3. Confusion Matrix

Precision: is a metric that signifies the proportion of true positives among all positive predictions made by the model:

$$precision = \frac{TP}{TP+FP} \tag{3}$$

Accuracy: serves as a performance measure for the model, indicating the percentage of correctly predicted samples (including true positives and true negatives) out of the total sample size. It offers a comprehensive evaluation of the model's accuracy in predicting both positive and negative samples:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

F1_score: is calculated as the harmonic mean of precision and recall, offering a balanced metric that takes into account both false positives and false negatives. This metric proves valuable, particularly in scenarios with class imbalances:

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$$F1 - score = 2 * \frac{precision*recall}{precision+recall} \quad (5)$$

Recall: referred to as sensitivity or true positive rate, measures the proportion of true positive predictions relative to the total number of actual positive samples. It indicates the model's capability to correctly identify positive samples among all the true positive samples:

$$recall = \frac{TP}{TP+FN} \quad (6)$$

Loss metric: is employed to assess the model's performance throughout the training phase. It measures the difference between the model's predicted values and the actual target values in the training data. Throughout training, the deep neural network strives to minimize this loss metric by iteratively adjusting its parameters (weights and biases), typically using techniques such as gradient descent or its variations. As the model learns from the data, the loss metric should ideally decrease over epochs, indicating that the model is converging to a solution that performs well on the training data.

Hardware and framework:

For this project, we opted for a machine running on the 64-bit operating system, Windows 10, with the following configuration: Intel® Core™ i5-8350U CPU @ 1.70GHz 1.90 GHz processor and 16 GB RAM. As for the framework, we chose Keras (n.d.), a high-level Python library, to interact with TensorFlow (n.d.), the machine learning framework developed by Google.

Methodology and Experience

In this section, we outline the systematic approach taken to execute the project. Python serves as the programming language, Jupyter Notebook functions as the web-based interactive computing platform, and Scikit-learn (n.d.) and Keras are employed as open-source libraries, serving as the implementation toolkit.

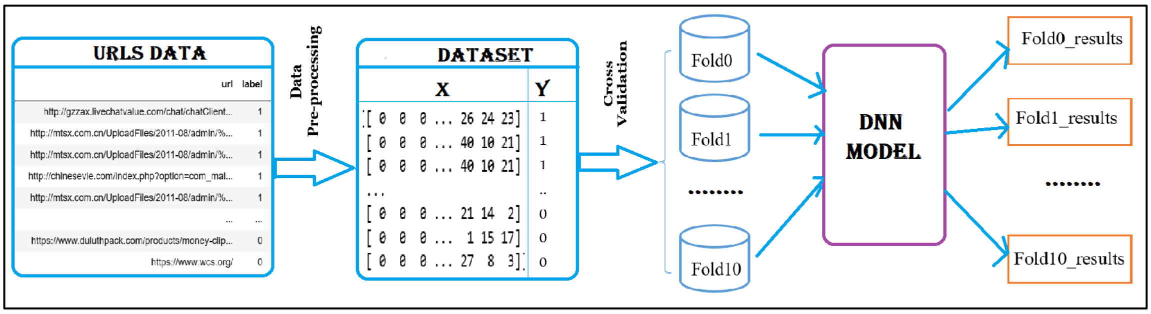

Figure 4. Summary of the proposed steps to implement our project.

URL data

To construct a Deep Neural Network (DNN) model designed for URL classification, it is essential to acquire a dataset comprising URLs along with their respective target labels or features. For this paper, we gather data on 40,000 URLs from two distinct sources: Mendeley

Data (n.d.) and the Kaggle platform (Kaggle, n.d.). URLs from these sources are categorized into two classes, where 20,000 phishing URLs are labelled with 1, and 20,000 benign URLs are labelled with 0.

Data preprocessing

To achieve effective training of the neural network, it is crucial to ensure that the data is in a suitable format. The subsequent steps outline common data preprocessing procedures, defined earlier.

Table 1. Python script of the utilized methods

Step	Python script
Data Cleaning	Data_set = pd.read_csv('dataf.csv') data_set = data_set.dropna()
Tokenizer	Tokenizer_url = Tokenizer(char_level=True) Tokenizer_url.fit_on_texts(urls) Seq_url = tokenizer_url.texts_to_sequences(urls)
Pad_sequences	max_sequence_length = max(len(seq) for seq in seq_url) seq_url = pad_sequences(seq_url, maxlen= max_sequence_length)

Cross-validation

Cross-validation is a technique employed for model validation, assessing the generalization performance of a statistical analysis on an independent dataset. It is particularly useful in predictive scenarios, such as estimating the accuracy of a predictive model in real-world applications. A popular variant in machine learning is K-Fold cross-validation, where the dataset is divided into k equal-sized folds. The model is trained on k-1 folds, with the remaining fold reserved for testing. In this study, "Repeated Stratified K-Fold cross-validation" was chosen. Stratified K-Fold ensures a balanced representation of target classes in each subset, and the term "Repeated" signifies the process's iteration for enhanced robustness (Bouijij & Berqia, 2021; Scikit-Learn, n.d.). The Python script in Figure 5 demonstrates the implementation of Repeated Stratified K-Fold cross-validation.

```
from sklearn.model_selection import RepeatedStratifiedKFold
RepeatedStratifiedKFold(n_splits=5, n_repeats=2, random_state=1)
```

Figure 5. RepeatedStratifiedKFold python script

Deep Neural Network model

We have proposed a DNN model that consists of a sequence of dense (fully connected) layers with decreasing output sizes (256, 128, 64, 1) until it reaches an output of dimension (batch_size, 1). See Figure 6.

Figure 7 illustrates the sequential model of the deep neural network that we have implemented.

```
# Import Keras library
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

# Create a sequential model
model = Sequential()

# Add a Dense layer
model.add(Dense(256, input_dim= max_sequence_length, activation='relu'))

# Add a Dropout layer with a rate of 0.2
# (each neuron has a 20 in 100 chances of being turned off in training)
model.add(Dropout(0.2))

# Add a Dense layer
model.add(Dense(128, activation='relu'))

# Add a Dense layer
model.add(Dense(64, activation='relu'))

# Add a Dense layer
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Figure 6. DNN python script

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 256)               33024

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 dense_2 (Dense)             (None, 64)                8256

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 74,241
Trainable params: 74,241
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. Proposed sequential model

Results and Discussion

We used the previously discussed methods and techniques, including data preprocessing and cross-validation, and computed evaluation metrics for each fold. Figure 8 outlines the outcomes of our experimentation.

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We note that the average precision varies within the range of approximately 93% to 99.70%, accuracy from 92% to 99.69%, F1_score from 90% to 99.59%, and recall from 87.42% to 99.47%.

	Fold	Precision	Accuracy	F1_score	Recall	Conf_Matrix
0	Fold0	0.930143	0.927125	0.901337	0.874261	[[4754, 200], [383, 2663]]
1	Fold1	0.966243	0.968125	0.957760	0.949425	[[4854, 101], [154, 2891]]
2	Fold2	0.981636	0.980000	0.973510	0.965517	[[4900, 55], [105, 2940]]
3	Fold3	0.990716	0.989375	0.985976	0.981281	[[4927, 28], [57, 2988]]
4	Fold4	0.988177	0.991000	0.988177	0.988177	[[4919, 36], [36, 3009]]
5	Fold5	0.991359	0.988875	0.985301	0.979317	[[4928, 26], [63, 2983]]
6	Fold6	0.992452	0.994500	0.992777	0.993103	[[4932, 23], [21, 3024]]
7	Fold7	0.997038	0.996875	0.995890	0.994745	[[4946, 9], [16, 3029]]
8	Fold8	0.996040	0.995125	0.993580	0.991133	[[4943, 12], [27, 3018]]
9	Fold9	0.993115	0.995375	0.993929	0.994745	[[4934, 21], [16, 3029]]

Figure 8. DNN model results

The best results were achieved with the dataset of Fold 7, demonstrating exceptional performance:

- Precision: 99.70%;
- Accuracy: 99.69%;
- F1 Score: 99.59%;
- Recall: 99.47%;
- Confusion matrix as follows:
    - True Positives (TP): 3,029 (properly predicted positive samples);
    - False Positives (FP): 9 (negative samples erroneously classified as positive);
    - True Negatives (TN): 4,946 (correctly predicted negative samples);
    - False Negatives (FN): 16 (positive samples incorrectly classified as negative);

These high metrics and the detailed confusion matrix indicate that the model achieved near-perfect classification on Fold 7, with a very small number of misclassifications.

In a similar manner, on Fold 7, we provide the graphs (Figure 9 and Figure 10) illustrating the accuracy function and loss function during the training process.

In Figure 9, it is evident that, throughout the 100 epochs of training the DNN model with the dataset derived from Fold 7, the loss metric consistently declined from an initial value of 0.020

to a final value of 0.009. The reduction in loss implies a continuous enhancement in the model's performance over the training period.

Figure 10 illustrates that the accuracy metric, monitored during the training process specifically on Fold 7, exhibited a significant improvement. Commencing at 99.30%, it steadily rose to attain a higher accuracy level of 99.75%. This upward trend in accuracy suggests that the model's ability to correctly classify instances improved during the training iterations on the Fold 7 dataset. The recorded increase in accuracy indicates a positive refinement in the model's performance, signifying its enhanced capability to make accurate predictions over the course of training.

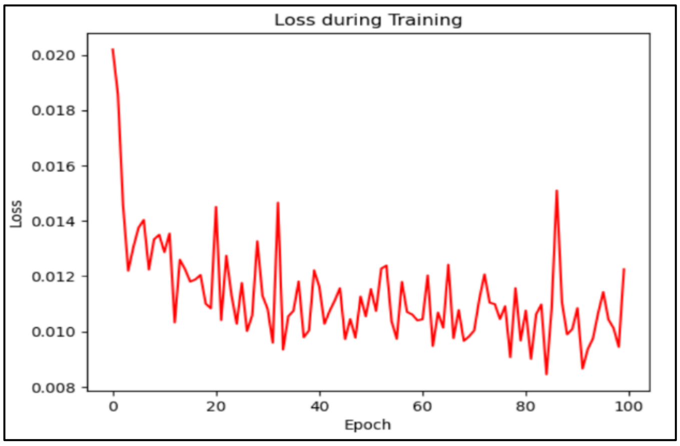

Figure 9. Loss metric recorded during the training process on Fold 7

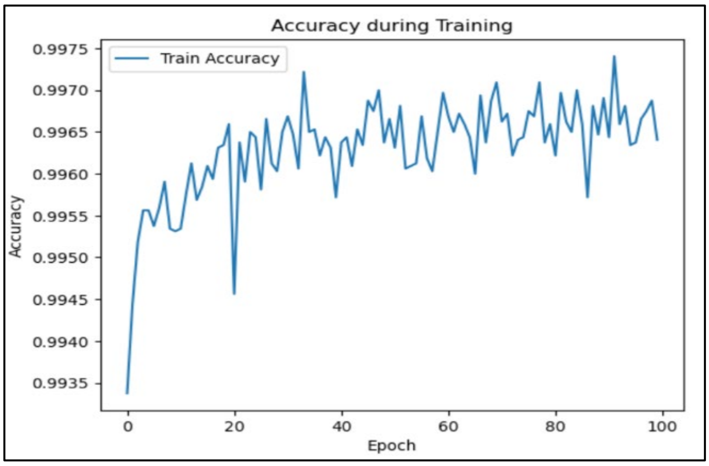

Figure 10. Accuracy metric recorded during the training process on Fold 7

Comparative Analysis

Table 3 presents a comparative analysis between our model and previously mentioned works, focusing on performance metrics related to the classification of phishing websites. The evaluated metrics encompass precision, accuracy, F1 score, and recall. Furthermore, the table provides insights into the utilized algorithms and the techniques applied for feature extraction in the respective studies.

Table 3. Comparison of our results and other work

Authors	Approach	Results
Sánchez-Paniagua *et al.*	-HTML, URL and web technology features -ML (LightGBM)	Accuracy of 97.95%
Adebowale *et al.*	-Features of images, frames and text -Adaptive Neuro-Fuzzy Inference System	Accuracy of 98.30%
Salah & Zuhair	URL and CNN-BiLSTM	Accuracy of 99%
Our paper	URL and DNN	The average precision ranges from approximately 93% to 99.70%, accuracy from 92% to 99.69%, F1_score from 90% to 99.59%, and recall from 87.42% to 99.47%

Conclusion and Future Work

In this work, we addressed the pressing concern of phishing attacks in the Internet of Things (IoT), focusing specifically on the smart home environment. As IoT devices become increasingly interconnected, the risk of cybercrime, particularly phishing attacks, has grown substantially. These attacks exploit users' trust to gather sensitive information, making it crucial to develop robust security mechanisms to safeguard IoT systems.

Our research explored various models proposed by researchers to counter phishing attempts in the IoT ecosystem. To enhance the cybersecurity of smart homes, we presented our novel methodology centred on Deep Neural Networks, incorporating tokenizer and pad_sequences data pre-processing techniques.

Through a comprehensive literature review, we contextualized the concepts of phishing and smart homes, while surveying existing works on phishing detection in IoT. Our experiment and methodology section detailed the techniques employed to develop our proposed model.

The obtained results demonstrated the effectiveness of our DNN-based model in detecting and preventing phishing attacks in smart homes, showcasing high evaluation metrics. Our model's performance was further compared to other related works, highlighting its competitive advantages.

In summary, this paper makes a valuable contribution to the growing body of research in IoT security and phishing detection, offering valuable insights into protecting IoT devices and systems. As the IoT continues to evolve, our proposed model presents a promising step towards enhancing cybersecurity and safeguarding users' sensitive information in the connected smart home environment.

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Ultimately, it is crucial to maintain security and ensure the efficiency of the phishing detection model by persistently collecting data and regularly training the model with the most up-to-date information.

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Implementation of a Cross-Platform Development Board for Embedded Internet-of-Things Systems

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Abstract: A prototype of a printed circuit board (PCB) with radio frequency electromagnetic compatibility specifications is designed using the top-down methodology for the two-layer Internet of Things with free open-source hardware and software, using the following techniques: requirements, analysis, modular design, schematics, manufacturing and functional testing. The study of the influence of the design parameters is carried out applying the standards of the Printed Circuit Institute and the characteristics of the technological production process for a free multiplatform for wireless networks. Finally, functional tests of the universal asynchronous transmit and receive (UART) communication with the microcontroller, the radio modules, the general-purpose input and output pins, and the over-the-air (OTA) configuration are performed to program the board wirelessly, without the need of a universal serial bus (USB) interface.

Keywords: Development, Internet of Things, embedded, board, wireless

Introduction

For the design and development of a printed circuit board, it is essential to take into account international standards. In this sense, when carrying out the research, the European platforms initiative is adopted as a reference. It is considered a reference framework oriented to the interoperability of Internet of Things (IoT) platforms, with the objective of simplifying the complexity of heterogeneous physical devices that support various communication protocols.

This simplification is achieved by implementing an intermediary gateway, which simultaneously manages the different platforms. Following the approach proposed by Vermesan (2018), this gateway enables interaction with a single IoT device, thus facilitating functionality between different layers and varied protocols. By adopting this strategy, it not only achieves greater consistency and simplicity in PCB design, but also opens the door to greater flexibility and adaptability in terms of technological evolution.

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This capability has been made possible by the dizzying growth in telecommunications, supported by advances in digital microelectronics, computing systems, and radio communication. These advances translate into increasingly efficient systems, both at the hardware and software levels, enabling the creation of highly energy-efficient wireless networks, as highlighted by Bloom *et al.* (2018) in their research.

In line with this technological evolution, the proposed design phase involves a thorough review and calculation of various metrics, such as track dimensions, print type, soldering components, and the cutting process of the material used in printed circuit boards (PCBs). This information is crucial in providing the designer and developer with a deeper understanding of the design process, allowing them, in turn, to verify and optimize their evaluation procedures, as described in the study by Razmhosseini *et al.* (2020). This meticulous approach not only ensures more accurate design execution, but also contributes to the continuous improvement of the PCB development process, adapting it to the latest industry trends and standards.

Mobile IoT systems are characterized by the presence of multipath channels, making use of the channel diversity technique in order to mitigate the degradation inherent in multipath and to maximize the gain in a specific direction through antenna terminals, as discussed in previous terminal studies (Balanis, 2016). This approach is implemented to achieve optimal impedance matching and a wide bandwidth.

Within the framework of this project, the use of external antennas, strategically selected, has been chosen for the purpose of guaranteeing that the aforementioned parameters are optimal to facilitate the communication process and the efficient coexistence of various wireless technologies, including Lora, Sigfox and ZigBee, as highlighted in recent research by Federico *et al.* (2021).

Literature Review

In the manufacturing process of a PCB as indicated by Silvestre *et al.* (2019), the following must be considered: various elements, such as the layout of signal and power supply tracks; the strategic placement of components; and the efficient management of grounding to achieve an effective design, as noted by Waage & Faero (2019).

A fundamental aspect in the design and functionality of PCBs is the ability of systems to interface without being affected by Electromagnetic Interference (EMI) (Yang *et al.*, 2019). In addition, Electromagnetic Compatibility (EMC) must be ensured, an aspect analyzed by Mehri (2021). Both aspects are critical to ensuring that the PCB performs efficiently in complex environments and diverse operating conditions at the proposed design time.

The importance of these aspects highlights the relevance of complying in the development of the AnaBit board (the name AnaBit arises from the fusion between 'Bit', the essence of digital technology and IoT communication, and a subtle personal tribute encapsulated in 'Ana') with the regulations established by IPC (IPC-2252 Task Group & High Frequency Design Task Group, 2002), which define specific rules for various types of systems in relation to EMI and EMC (Sis *et al.*, 2022). Depending on the specific application, it becomes imperative to comply with these regulations in the design of a PCB.

Proper arrangement of electronics on the PCB can not only significantly mitigate EMI but can also improve EMC (Razmhosseini *et al.*, 2020). This technical approach to PCB design improves performance, stability and reliability in varied operating environments.

In the PCB design process, the essential aim is to ensure optimum quality and functionality (Khandpur, 2016). An innovative approach to this process focuses on Laser Direct Imaging (LDI) technology (Eisenbarth *et al.*, 2019), which consists of analyzing the impact of a focused laser beam to directly expose PCB panels, eliminating the need for traditional photographic tools, thereby reducing repeated defects and low dimensional stability, which can result in a decrease in signal propagation delay time and the presence of electromagnetic noise.

Additionally, Tatariants *et al.* (2018) explore sputtering operations that take extensive advantage of waste printed circuit board recycling (WPCB). This method aims to release metal and glass fibre in powder form from waste PCBs, thus contributing to more sustainable and eco-friendly practices in the manufacturing process, improving the efficiency and quality of the final product, as well as addressing environmental concerns by leveraging recycled resources. For the design of the AnaBit board, established standards and their application are taken into account to ensure optimal quality and functionality of the final products (Silvestre *et al.*, 2019).

In complementary research, Tran *et al.* (2018) focus on the detailed study of graphene inks and various printing techniques, such as screen printing, etched hollow, inkjet, and other emerging printing technologies. This comprehensive study seeks to identify and evaluate the most suitable types of conductive inks for the manufacture of printed flexible circuits. This analysis contributes to the improvement of the printing processes used in PCB production, allowing an informed selection of materials that optimize circuit conductivity and efficiency.

In the study conducted by Babos *et al.* (2020), both the limitations and advantages inherent in the calibration process aimed at reducing PCB board waste samples are detailed. As discussed by Vasilyev *et al.* (2021), this research supports addressing matrix effects and ensuring accurate calibration in the manufacturing process for quality improvement in waste management.

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Also, when considering copper lamination and dimensional changes in the process, copper traces and holes are created with extraordinary precision on the circuit board to facilitate the proper connection of electronic components (Sathyakumar *et al.*, 2018).

In line with the practices recommended by Dong *et al.* (2018), when implementing double-sided printing, the Direct Write Deposition (DIW) technique is incorporated, followed by drilling and filling processes. This approach is crucial for creating complex circuit structures and ensuring robust connections. In addition, the conductive wiring material must meet stringent requirements in terms of electrical conductivity, mechanical reliability, and processability to ensure efficient and sustainable circuit operation.

Material and Methods

Card design and development methodology

The research adopts a quantitative approach based on its methodological orientation. In line with its purpose, the study follows an experimental design (Hernández Sampieri *et al.*, 2018). This approach allows for a more comprehensive and in-depth understanding of the investigated phenomena, aligning with the recommendations of Vasilyev *et al.* (2021). This methodology entails the management of experimental variables to analyze their impact on the development of IoT embedded systems, as emphasized by De Nardis *et al.* (2022). The study applies international design standards to ensure a rigorous and standardized evaluation of the subject matter.

Through a rigorous and systematic study, the stages are determined that allow evaluating the design at each step, making adjustments and corrections for possible failures, and continuously improving the design. By applying the Top-Down technique (Care *et al.*, 2017), an effective and efficient approach is achieved for the synthesis of the idea with a high level of abstraction and in its progressive implementation, to increase the level of detail as needed (Rivadeneyra *et al.*, 2022). By decomposing the initial system into modules, a hierarchy is established that allows a modular and functionally independent structuring of the design, as shown in Figure 1.

Identification of requirements

A description of the group of IoT technologies is made according to the market trend; among the most known are WirelessHART, Sigfox, NB-IoT, LonWorks, NB-FI, LoRaWAN, KNX, BLE Mesh, Bluetooth, CAT-M1, ZigBee, Thread, Z-Wave, Dash7 and Wi-Fi.

Google's search engine analysis tool, Google Trends, is used and non-IOT technologies Wi-Fi, Bluetooth, KNX and Thread are discarded. The result of the analysis is presented in Figure 2.

This analysis approach allowed us to accurately identify the popularity of IoT technologies that are not yet in common use compared to those that are already widely known (Qadir *et al.*, 2023).

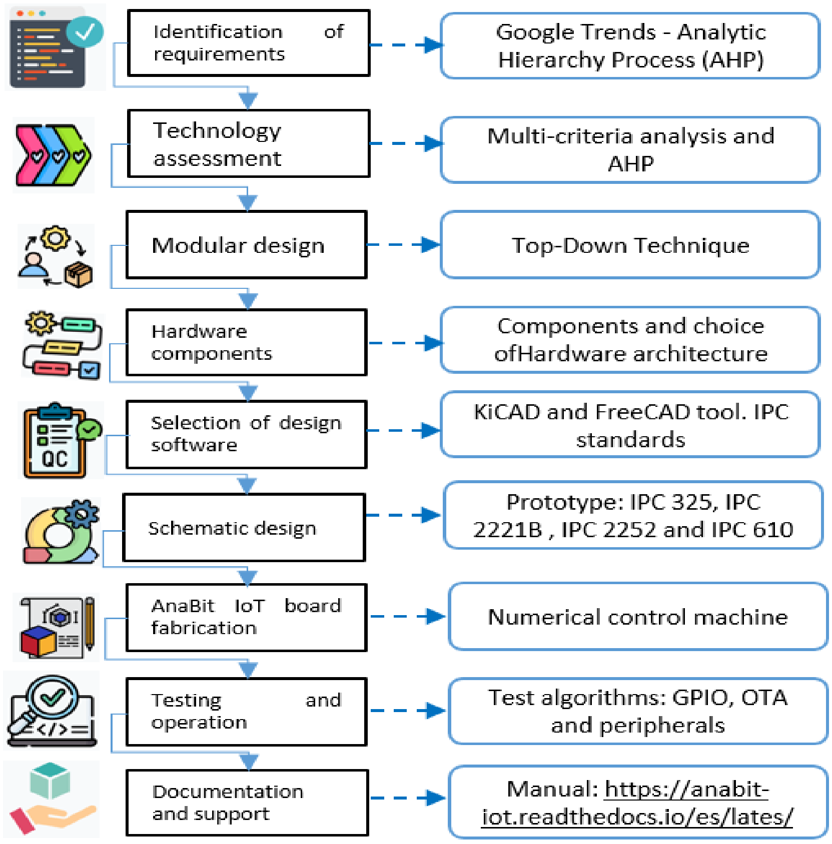

Figure 1. Design methodology: IoT development board (Source: Authors)

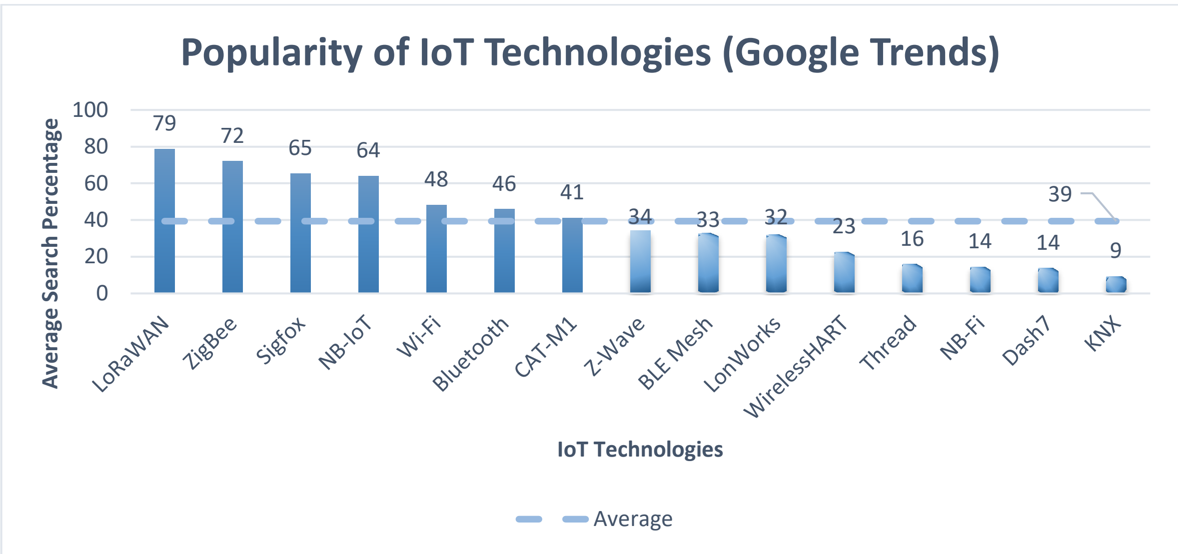

Figure 2. Popularity of IoT technologies (Source: Authors)

To select those to be used in the design of the development board, the top 7 IoT technologies that were above the global market average were taken as a starting point: LoRaWAN, ZigBee, Sigfox, NB-IoT, Wi-Fi, Bluetooth and CAT-M1.

A multi-criteria analysis is then used according to the factors of compatibility, scalability, network coverage, transmission speed, power consumption, security and ease of integration for the creation of an IoT development board. Weights are then assigned to these criteria using the Analytic Hierarchy Process (AHP) method (Ho & Ma, 2018), as seen in Table 1.

Table 1. AHP criteria comparison matrix (Source: Authors)

Identified Criterion	Compat ibility	Scalab ility	Network coverage	Transmiss ion speed	Power consumption	Secur-ity	Ease of integrat-ion
Compatibility	**1**	5	2	7	3	1	1
Scalability	1/5	**1**	1/5	1/4	1/5	1/8	1/9
Network coverage	1/2	5	**1**	3	1/4	1/5	1/4
Transmission speed	1/7	4	1/3	**1**	1/3	1/6	1/5
Power consumption	1/3	5	4	3	**1**	1/2	1/3
Security	1	8	5	6	2	**1**	1
Ease of integration	1	9	4	5	3	1	**1**

Numerical values are assigned to each cell to reflect the relative importance of each criterion in relation to the others, where “1” indicates that two criteria are equally important and 9 indicates that one criterion is extremely more important than another. Subsequently, its eigenvector is calculated (see Table 2), with the percentage of importance assigned to each criterion evaluated.

Table 2. Eigenvector of the AHP criteria comparison matrix

Identified Criterion	Own Vector	Percentage
Compatibility	0.2273	**22.7281**
Scalability	0.0241	2.4135
Network coverage	0.0788	7.8782
Transmission speed	0.0446	4.4558
Power consumption	0.1309	13.0911
Security	0.2451	**24.5053**
Ease of integration	0.2493	**24.9280**

The comparison matrix of the data in Table 1 is obtained empirically according to the qualitative assessment of the research, and the values of the significant weights are assigned by the degree of importance of market trends and technological advancement in order to determine the identification of the criterion. It is important to note that, if in the comparison of two criteria the value of one cell is x, then, in the inverse comparison, the value of the corresponding cell should be 1/x to maintain consistency in the criteria comparison matrix. This ensures that the matrix is consistent and adequately reflects the relative importance of each criterion. Once the criteria comparison matrix was obtained, its eigenvector was calculated. Table 2 shows the result of this calculation, associated with the percentage of importance assigned to each criterion evaluated.

Initially, λ_{max} is defined, which is the indicator of how consistent the pairwise comparisons are within the comparison matrix in the AHP methodology. To calculate λ_{max}, we first obtain a vector of averages per row from the criteria comparison matrix. Then, we multiply the criteria matrix by this vector, generating a row vector (VF). We apply equation (1) to obtain a vector of quotients (VC). Finally, we calculate the average VC using equation (2) to obtain the value of λ_{max}:

$$VC_i = \frac{VF_i}{VP_i} \tag{1}$$

$$\lambda_{max} = \frac{\sum_{k=1}^{n} VC_k}{n} \tag{2}$$

To verify the consistency index (CI), equation (3) is used to ensure that the comparison matrix is consistent and reliable for further analysis and decision-making (Nasution *et al.*, 2018):

$$CI = \frac{\lambda_{max} - n}{\text{n}-1} \tag{3}$$

The variable λ_{max} refers to the maximum eigenvalue of the criteria comparison matrix, while n represents the size of this matrix (the matrix has n rows and n columns). With equation (4), the consistency ratio (CR) is found (Nasution *et al.*, 2018):

$$CR = \frac{\text{CI}}{\text{RI}} \tag{4}$$

In equation (4), Table 3 provided by the AHP method is used, which gives the random index (RI) as a function of the size of the matrix. This index is used in the calculation of the consistency ratio (CR) in order to check whether the values obtained in the criteria comparison matrix are coherent and conform to the consistency criteria established by the method.

Table 3. Random Index (RI)

Matrix Size	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random Index	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Once the CI and CR values have been calculated using equations (3) and (4), respectively, we proceed to compare the consistency ratio obtained with the values provided in Table 4, which provides consistency ratio values as a function of the size of the criteria comparison matrix. In the case in question, where the size of the matrix is greater than 4, the consistency ratio should be equal to or less than 10% to ensure that the matrix values are consistent and reliable for use in analysis and decision-making. This information can be seen in Table 4, given by the AHP method.

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Table 4. Allowable consistency ratio percentages

Matrix Size (n)	Consistency Ratio
3	5%
4	9%
5 or greater	10%

Therefore, when calculating the consistency index and consistency ratio values of the criteria comparison matrix, the values obtained, shown in Table 5, indicate that the matrix is consistent. This means that the evaluation of the criteria is correct and reliable for subsequent use in analysis and decision-making.

Table 5.I Consistency values of the criteria comparison matrix

λ_{max}	**7.7807**
CI	0.1301
CR	0.0986
CR Allowed	0.10

Technology evaluation

During this stage, a thorough and systematic evaluation is conducted to ascertain the option that aligns most closely with the predefined criteria. The Analytic Hierarchy Process (AHP) method proves valuable in this context, since it enables the comparison and weighting of criteria, facilitating well-informed decision-making, as illustrated in Table 6.

Table 6. Eigenvectors of the comparison matrices of alternatives by criterion

Identified Criterion	Compatib-ility	Scalability	Net-work cover-age	Transmiss-ion speed	Power consump-tion	Secur-ity	Ease of integrat-ion
Alternative s	**Own Vectors**						
LoRaWAN	0.3446	0.1661	0.4332	0.0318	0.3743	0.3104	0.3527
ZigBee	0.1846	0.4144	0.0892	0.0731	0.1582	0.2493	0.2465
Sigfox	0.1689	0.0425	0.1828	0.0201	0.2428	0.1125	0.0608
NB-IoT	0.0393	0.0434	0.1175	0.0846	0.0742	0.1072	0.0283
Wi-Fi	0.1825	0.2707	0.0457	0.3893	0.0194	0.1341	0.1672
Bluetooth	0.0596	0.0243	0.0190	0.2722	0.0824	0.0208	0.1148
CAT-M1	0.0205	0.0386	0.1127	0.1288	0.0489	0.0656	0.0296

After obtaining the eigenvector matrix of the comparison of alternatives for each criterion, it is multiplied by the weighting of the eigenvector corresponding to the comparison of criteria.

At the end, all the eigenvectors of each alternative are joined, creating a matrix, which is multiplied by the eigenvector of the criteria comparison, as shown in equation (5):

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$$A_{ij} = \sum_{k=1}^{n} B_{ik} C_{kj} \quad (5)$$

where A is the result, which is a matrix with the same number of rows as the eigenvector matrix corresponding to the comparison of criteria in matrix B and the same number of columns as the eigenvector matrix of the comparison of alternatives for each criterion in matrix C. The final result of the multi-criteria analysis using the AHP method is summarized in Figure 3.

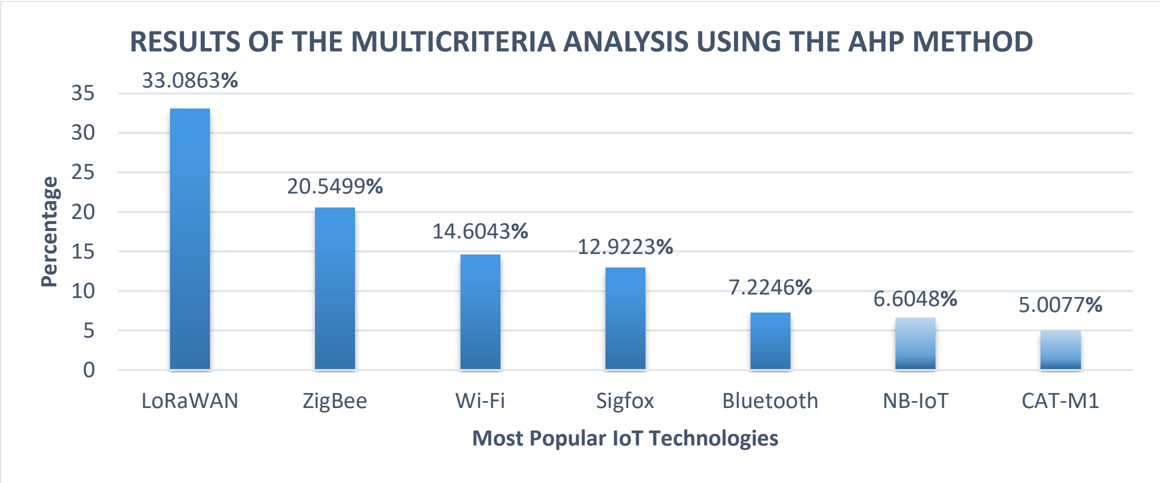

Figure 3. Multi-criteria analysis results using the AHP method (Source: Authors)

The top five technologies meet, in high percentage terms, the criteria identified for the selection of IoT technologies to be implemented on the development board with LoRaWAN, ZigBee, Wi-Fi, Sigfox and Bluetooth in addition meeting the top 7 requirements stated above.

Modular design

To establish the design steps, the methodology for the development of embedded hardware and software in safety-critical systems has been taken as a reference, since it shares similarities with the Top-Down methodology, with a mixed approach to obtain a more complete and deeper vision of the phenomena investigated on the addressed topic (Wang *et al.*, 2019). The application of the Top-Down methodology consists of the following stages: 1) definition of specifications; 2) global design (decomposition of the system into modules); 3) detailed design (decomposition of each module into submodules); and 4) modular integration.

1) Specification definition: the design focuses specifically on IoT. For this purpose, the following conditions are established: a) data processing system — to have adequate processing capacity to run algorithms and applications related to IoT; b) ability to interact with other devices — it must be able to interact through wireless technologies or through physical interfaces, such as GPIO ports; c) ability to be programmed — to allow application programming and implementation of control logic for connected IoT devices, through UART (Universal Asynchronous Receiver-Transmitter) or USB (Universal Serial Bus).

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Additionally, it has the characteristics of: d) wireless communication system — to incorporate a wireless communication system, which allows it to connect to WPAN, WLAN and LPWAN networks; e) data storage system — it can be in the form of internal memory or an external device; and f) energy efficiency — energy consumption should be optimized to prolong battery life and reduce energy consumption.

2) Overall design: involves the decomposition of the overall system into specific modules, such as processor and memory, inputs and outputs and communication interface. For the development, the following modules are integrated: a) wireless connectivity — LoRaWAN, ZigBee, Wi-Fi, Sigfox and Bluetooth; b) the external storage interface, by means of EEPROM or Flash memory; c) the power interface to facilitate operation with power adapters, batteries or alternative power sources.

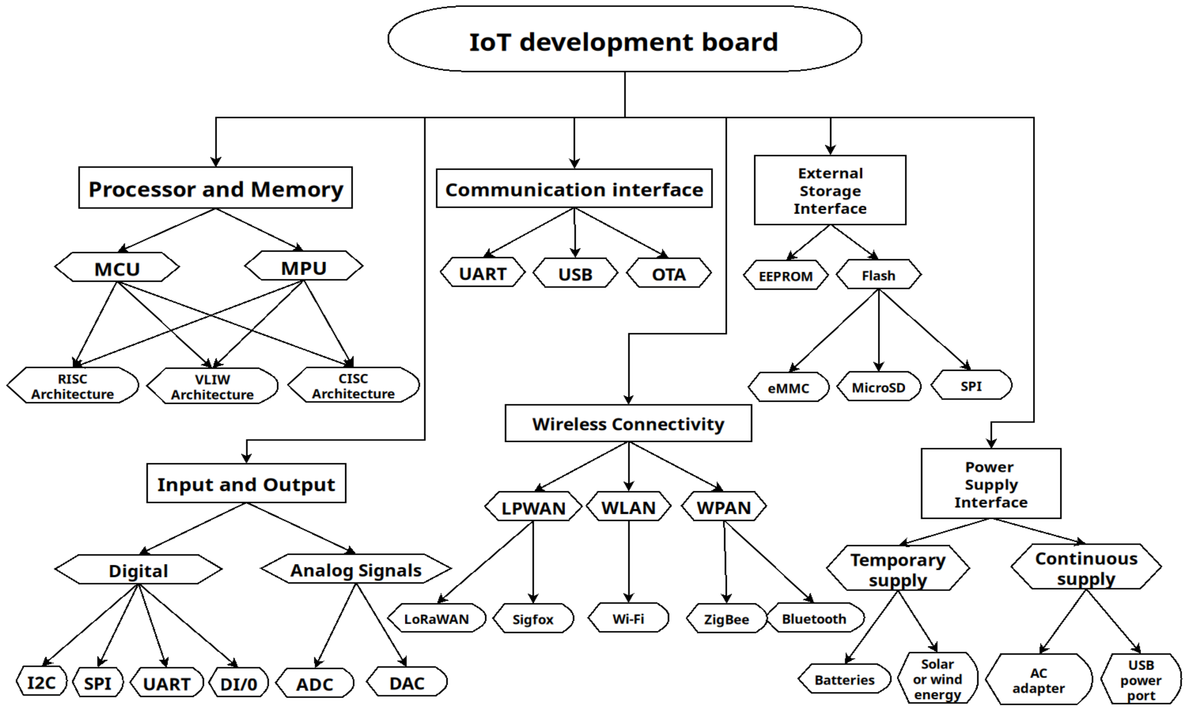

Figure 4. Top-down diagram of an IoT development board (Source: Authors)

3) Detailed design: To achieve a level of detail, it is necessary to decompose the previously designed modules into smaller submodules; and these in turn into other submodules of even lower level in order to describe internally the board design, as shown in Figure 4, where the processor and memory are identified with their respective architecture, the inputs and outputs, the communication interfaces — UART (Universal Asynchronous Receiver-Transmitter), USB (Universal Serial Bus) and OTA (Over-the-Air) — the wireless connectivity, the external storage interfaces, and the power supply module.

4) Modular integration: for the design of the complete system, the general requirements for the creation of the modules and submodules that were integrated in Figure 4 are considered following the Top-Down methodology.

Hardware components

The choice of CPU architecture will be based on two main criteria (Ojo et al., 2018): power consumption; and popularity in embedded systems where such architectures are implemented. RISC architecture is the most popular and consumes less power compared to VLIW and CISC architectures (Dudhane & Ravi, 2019), which have also been used in embedded projects (Marwedel, 2011), but their popularity is low and their power consumption is relatively high. The most relevant ones were consolidated according to their characteristics, as described in Table 7.

Table 7. Comparison of data processing hardware

Features			ATmega32u4		ESP32-WROOM-32		Allwinner H3 Cortex-A7		Rockchip RK3399 Cortex-A72 + Cortex-A53	
Device Type			MCU		MCU		MPU		MPU	
CPU Architecture			RISC		RISC		RISC		RISC	
Inputs/Outputs	DI/O		26		32		28		28	
	PWM		14		28		2		2	
	I2C	Modules	1		1		2		2	
	SPI		1		2		1		1	
	UART		1		3		3		1	
	ADC	modules	1	10 bits	2	12 bits	-	-	-	-
		Channels	12		16		-		-	
	DAC	modules	-	-	1	8 bits	-	-	-	-
		Channels	-		2		-		-	
CPU Working Frequency			16 MHz		240 MHz		1.6 GHz		1.8 GHz	
Number of cores			1		2		4		6	
Communication interface for programming			USB/UART		UART/OTA		UART		UART	
Data storage	EEPROM		1	512 bytes	1	512 bytes	-	-	-	-
	FLASH		-	-	1 flash SPI	4 MB	-	-	-	-
Wireless connectivity			-		Wi-Fi/ Bluetooth		-		-	
Working Voltage			2.7 - 5.0 - 5.5		2.7 - 3.3 - 3.6		1.4 - 3.3 - 3.8		1.8 - 3.3 -3.4	
Average Power Consumption			27 mA		500 mA		1.9 A		1.81 A	
Chip Cost (USD)			$38,520		$15,211		$51,249		$218,868	

For the selection of the chip for the IoT development board, four options were considered: two MCUs — ATmega32U4 and ESP32-WROOM-32 — and two MPUs — Allwinner H3 and Rockchip RK3399. It is observed that the MPUs are deficient in measuring analogue signals from their physical environment, since they require external electronics to do so. The selection

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of the ESP32-WROOM-32 chip facilitates wireless connectivity (Balanis, 2016), integrates the UART interface for programming, has Bluetooth and Wi-Fi connectivity; and the latter uses the OTA interface to program and update the MCU firmware wirelessly (Kocer *et al.*, 2021). When choosing radios for the remaining technologies, specific modules were chosen to cater to the unique requirements of each. For LoRaWAN technology, the RHF78-052 radio module was selected owing to its commendable sensitivity in both operational bands and its versatility in functioning across two different bands.

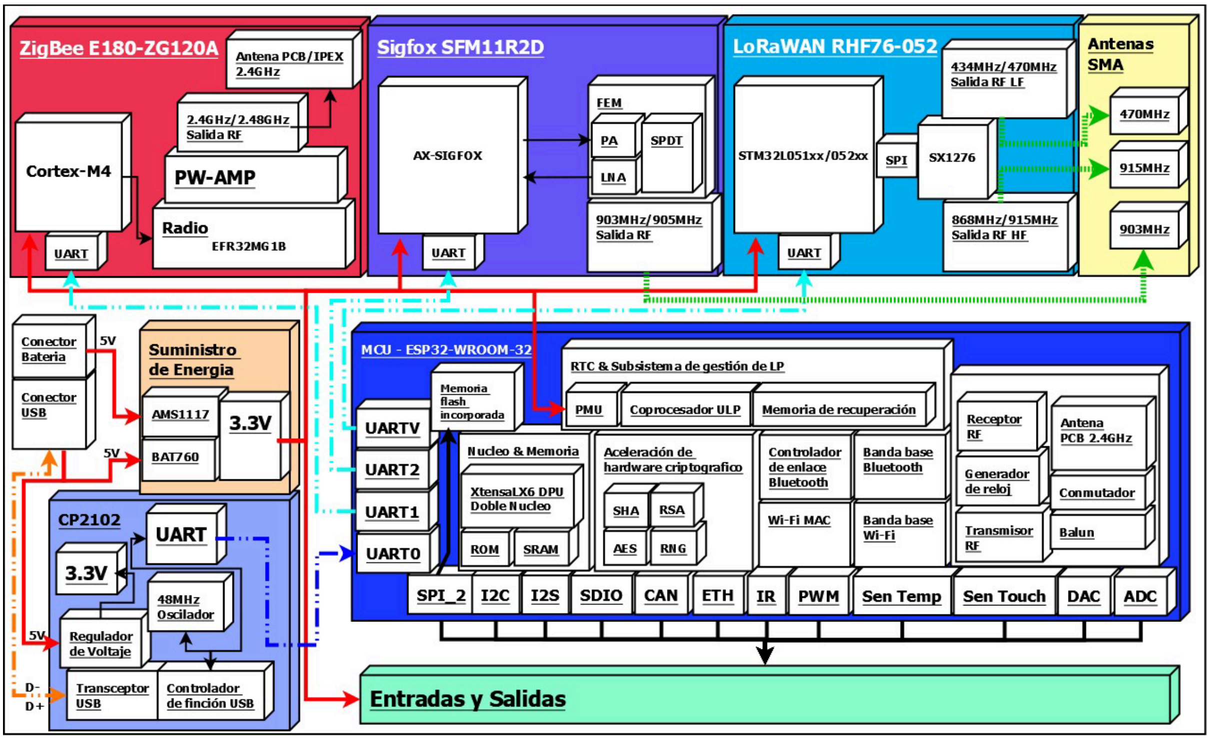

Figure 5. Hardware architecture of the IoT development board (Source: Authors)

For the Sigfox radio module, the WISOL SFM11R2D (Kocer *et al.*, 2021) stands out due to its low power consumption and signal sensitivity of -124 dBm and its compliance with the RC2 technology regulation for the Latin American area, with frequencies in the range of 902.2 MHz to 905.2 MHz. For the ZigBee modules, the E180-ZG120A module is chosen, which has the advantage of configuration as any type of node (Coordinator, Router and End Device) and the highest transmission power and range.

Figure 5 shows the integration of the complete hardware architecture distributed in sections and the indications of the signals to perform the control and communication between the technologies used in the assembly of the development board. The red lines show the communication process between the different technologies and the control of the MCU, which is in charge of managing all the processes together with the PMU in a centralized way. In the same way, the MCU supervises the inputs and outputs of the system; in the light blue lines, the MCU controls the UART module; the power supply uses 5 volts; and in the orange dashed line, the CP2102 converter establishes the communication between the PC and the microcontroller using the USB protocol. The continuous green lines indicate the access of each antenna module according to the working frequency.

Design software selection

The computer-aided design (CAD) software selection criteria focus on schematic creation, PCB layout, and 3D modelling of the final design. After evaluating the functionality requirements, three possible CAD software options have been identified: EAGLE, Altium Designer and KiCAD. The first is paid software, and its license can be expensive; the second is high-end, very complete and expensive; therefore, KiCAD is selected, since it is open source, accessible and, while the learning curve is steeper than for EAGLE, it facilitates the creation of high-quality and accurate designs. The design of the 3D modelling of the hardware components was complemented with FreeCAD (Machado *et al.*, 2019).

Schematic design

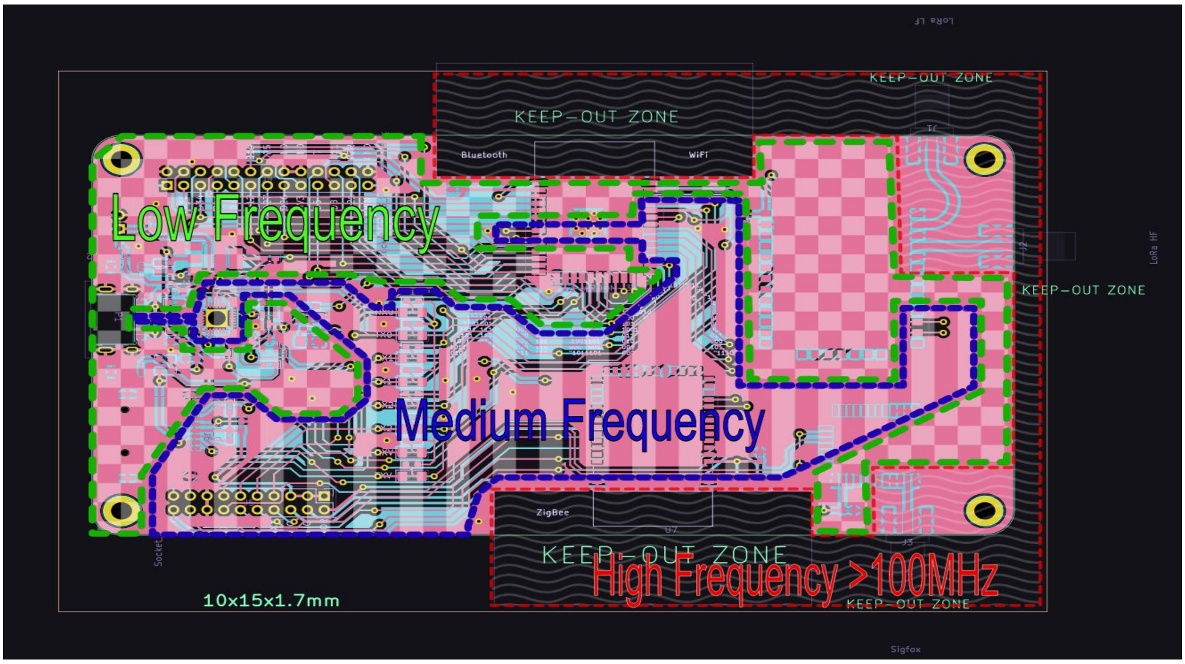

Figure 6. Separation of circuits according to IPC (Source: Authors)

The IPC 325 standard is established, considering the requirements for the documentation of printed circuit boards and printed circuit assemblies. The schematic design preview is shown in Figure 6, and compliance with electrical rules (ERC) was verified using KiCAD software (Dalmaris, 2021). With IPC 2221B (Guz, 2021) and IPC 2222 (Onshaunjit & Srinonchat, 2022), the design types and definition of rigid organic printed plate structures are classified (Razmhosseini *et al.*, 2020). Similarly, IPC 2252 is a reference for determining guidelines and specifications for Radio Frequency electromagnetic compatibility, as shown in Figure 6.

Finally, IPC 610 deals with the acceptability of electronic assemblies, verifying the quality of soldering and assembly (Khandpur, 2016).

In PCB design (Khater, 2020), circuits should be separated by function into three components: source circuit, analogue circuit, and digital circuit. In the particular case of the digital circuit, it should be separated by frequency into low, medium and high. The connectors should be as close as possible to the high-frequency circuit to avoid electromagnetic problems (Scheipel & Baunach, 2019).

AnaBit IoT board fabrication

The manufacturing process of the AnaBit IoT board involves a detailed examination of the machine's tools, techniques, and tolerances utilized. In the fabrication phase, a computer numerical control (CNC) machine (Mukrimaa *et al.*, 2016) was employed for tasks such as drilling, milling, laser screen printing applications, and the removal of the solder mask on the PCB pads. The manufacturing stage is summarized in Figure 7.

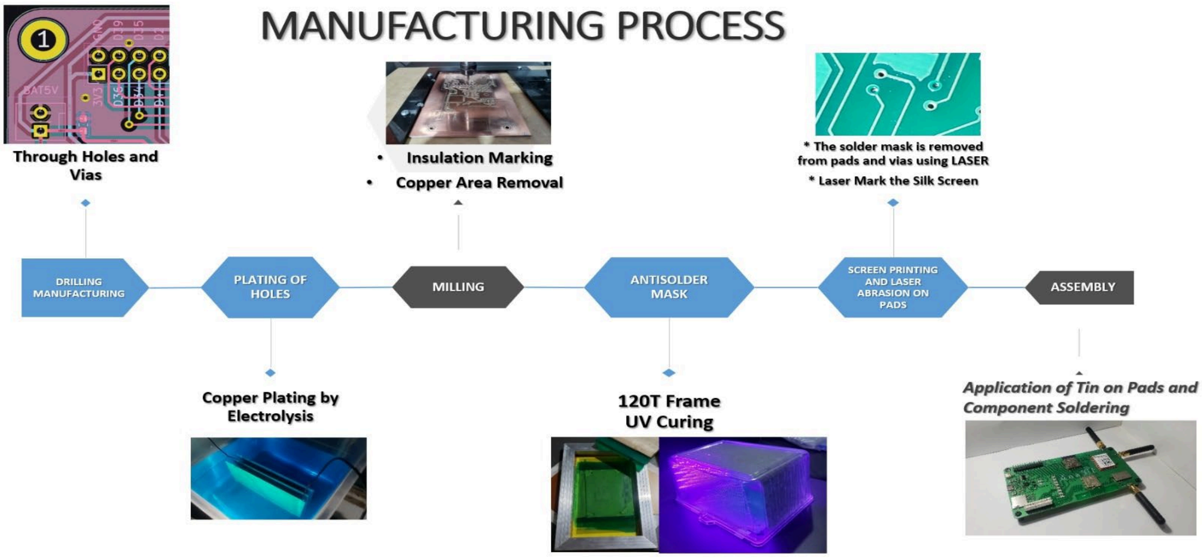

Figure 7. Manufacturing process

Figure 8. IoT development board (Source: Authors)

The decision to use lead-free tin solder was based on its simplicity and effectiveness, taking into account compliance with the RoHS (Restriction of Hazardous Substances) registration requirements for assembly and application on the pads. Figure 8 provides a visual representation of the AnaBit development board in its final state, as presented by Khater (2020).

Testing and operation

The correct UART communication test was performed between the MCU and the radio modules by means of an algorithm to check the activity of the GPIO pins. To configure the OTA interface on the AnaBit IoT development board, the following steps should be followed. First, in the Arduino IDE development environment, select the device name as "DOIT ESP32 DEVKIT V1". Then, the OTA interface configuration algorithm is compiled, which establishes the connection to a private network by providing the Wi-Fi credentials of the place where the board will be used, as shown in Figure 9, and proceeds to send data to check connectivity and functionality.

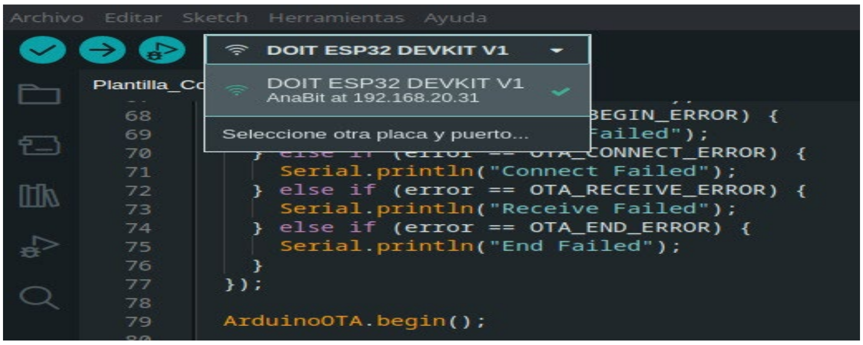

Figure 9. Programming port via OTA interface (Source: Authors)

Documentation and support

A user manual, structured as a wiki, was developed and is available on the website https://anabit-iot.readthedocs.io/es/latest/. Users can find the guide with all the detailed information on use, configuration and functionalities of the AnaBit card.

Results

The following is a series of test algorithms that can be used to verify the correct operation of the AnaBit IoT development board.

UART communication test algorithm

A test was performed to verify correct UART communication between the MCU and the radio modules, as shown in Figure 9.

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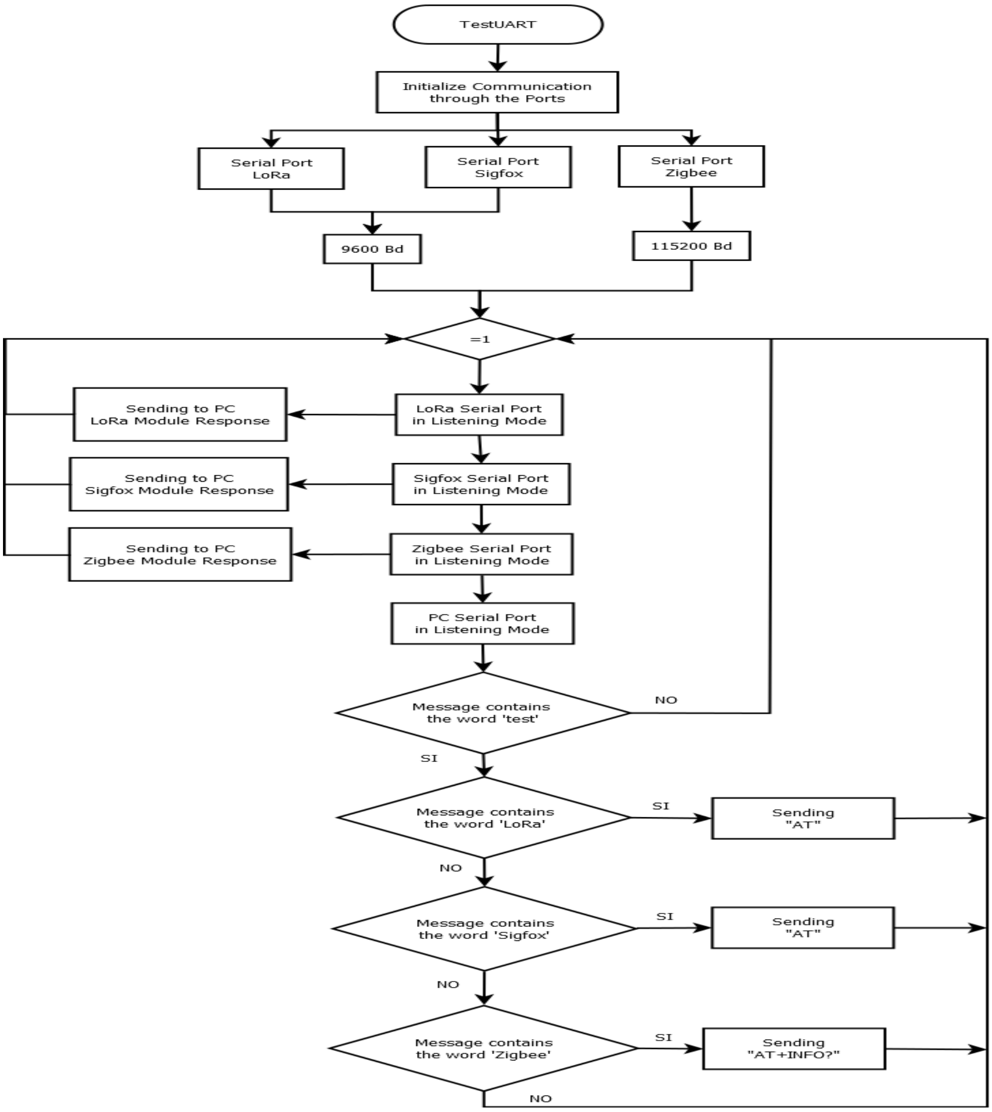

Figure 9. UART communication test algorithm (Source: Authors)

MCU GPIO pins test algorithm

The serial port was used to indicate which GPIO pin is configured as a digital output pin; physically, LEDs were connected to each of the GPIO pins on the corresponding terminal strip to individually test each pin, as shown in Figure 10.

Configuration for programming the AnaBit via Wi-Fi

First, in the Arduino IDE development environment, select the device name as “DOIT ESP32 DEVKIT V1”. Then, compile the OTA interface configuration algorithm, which establishes the connection to a private network by providing the Wi-Fi credentials of the location where the board will be used. After the connection is established, use the OTA libraries to configure the MCU memory allocation, as shown in the flowchart in Figure 11. Once the configuration code has been successfully uploaded, it is not necessary to use the USB interface to program AnaBit.

With this OTA configuration, remote updating and uploading of algorithms to the AnaBit development board is facilitated, without the need to physically connect the board to the PC every time a modification is made to the code. This provides flexibility and agility in the development of projects and allows a quick implementation of changes or improvements on the board.

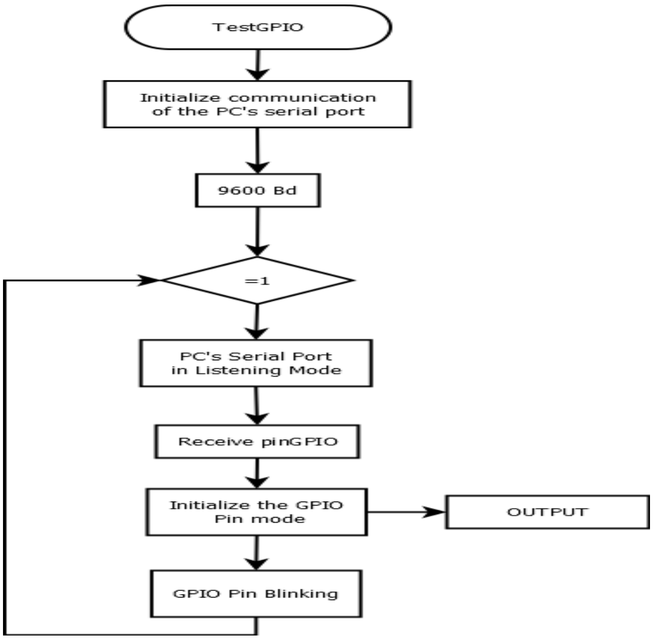

Figure 10. GPIO pin test algorithm (Source: Authors)

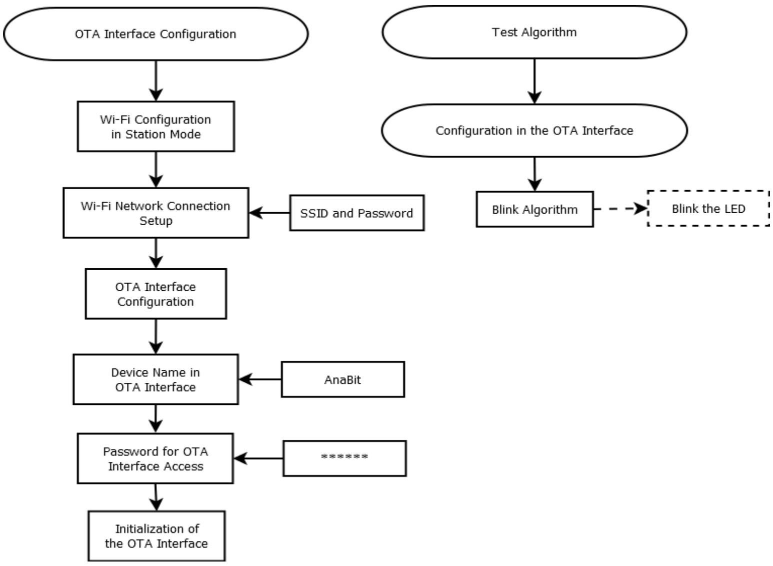

Figure 11. OTA interface initialization algorithm (Source: Authors)

Communications by technologies

A point-to-point LoRa network is created with two AnaBit cards. For “Card A”, the message is transmitted at 915 MHz and the response is received from “Card B” at 470 MHz. In the opposite direction, for “Card B”, it transmits at 470 MHz and receives messages from “Card

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A" at 915 MHz. This takes advantage of the use of both antennas and optimizes the bandwidth in the link (see Figure 12).

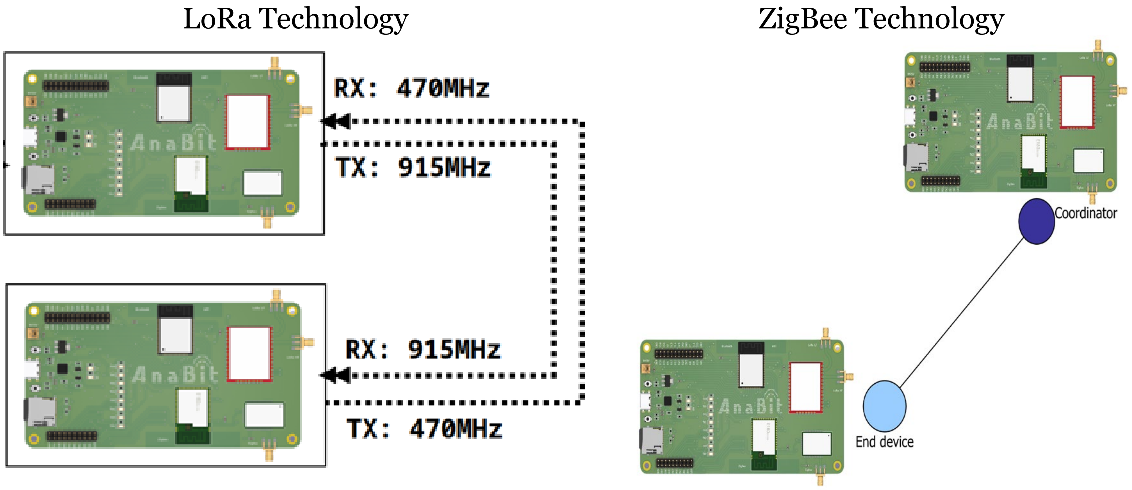

Figure 12 Example of LoRa and ZigBee communication (Source: Authors)

For the ZigBee communication example, a connection is created between a Coordinator and an end device using two AnaBit cards. This configuration can be extended to a more complete mesh network with 10 or 100 AnaBit cards, emphasizing that it is possible to work in the following modes: coordinator, router, or end device.

Conclusion

The hardware development process proves to be a fundamental step in the identification and selection of viable and promising technologies in the area of the IoT. The implementation of strategic filtering, using Google Trends to assess the popularity of IoT technologies, combined with a multi-criteria selection method, has proven to be key to the optimal selection of the most appropriate technologies for the AnaBit development board project. This means that it provides valuable insight by providing real-time data on the popularity and trends of IoT technologies, thus enabling informed decision-making by using multiple criteria to add robustness to the research process.

This combined approach also ensures optimal compliance with the particular objectives and requirements of the AnaBit development board, taking into account aspects such as scalability, interoperability and long-term technical feasibility.

The design requirements have been achieved through the use of highly specialized software tools for the design, simulation and printing of printed circuit boards, with meticulous adherence to minimum manufacturing tolerances and dispensing with manual interventions. This approach has significantly streamlined the transition to the manufacturing phase. In addition, rigorous adherence to IPC standards has established a solid frame of reference to ensure consistency between the design and manufacturing stages, guaranteeing optimal

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electrical performance and ensuring the achievement of electromagnetic compatibility, crucial elements for the board's long-term performance and stability.

In the manufacturing phase, the efficient and accurate use of open-source software for the generation of the G-Code files required for interpretation by the CNC machine has been demonstrated. Accuracy in the positioning of the machine and the cutting diameter of the milling cutter have proved to be decisive factors in achieving the required quality of the tracks and pads. In addition, an adequate density of points in the height map has been ensured, which contributes significantly to the quality and accuracy of the process.

The implementation of plating methods has significantly streamlined the manufacturing process, as has the application of the anti-solder mask and the creation of laser screen printing, providing a high-quality professional finish. Crucially, due to the inherent limitations of the CNC machine, fabrication is carried out on an individual basis, thus orienting the process more towards a prototype approach rather than mass production. This individualized approach ensures meticulous attention to detail and precise adaptation to design specifications, despite the limitations of the machinery used.

Algorithm implementation has played a key role in simplifying the evaluation of the communication between the Central Processing Unit (MCU) and the radio modules, as well as the testing of the General Purpose Input/Output pins, including those dedicated to UART communication between the MCU and the radio modules. In addition, the OTA interface configuration has opened up new possibilities by allowing remote programming of the AnaBit board via a Wi-Fi connection, eliminating the need to rely exclusively on the USB interface, especially in situations where physical access to the board is difficult.

The research not only optimizes the evaluation and testing processes but also offers greater flexibility and accessibility in card programming, marking a significant milestone in the evolution of the AnaBit card. The integration of these technologies not only simplifies management and optimizes efficiency, it also establishes an advanced standard for future developments in the interface and programming of IoT devices, increasing the versatility and usability of the card in different contexts and operating scenarios.

In short, rigorous quality control, backed by recognized standards, and detailed research on graphene inks and printing techniques represent crucial steps in raising quality and efficiency in PCB production. The research made it possible to find precise and advanced approaches in the manufacture of PCBs, highlighting aspects such as calibration, precision in manufacturing, the appropriate choice of materials, and the optimal performance of electronic devices.

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Natural Language Processing for Detecting Brand Hate Speech

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Abstract: Brand hate is a complex feeling that is not easy for companies to recognize. Mednini and Turki (2022) have confirmed that the hate can originate from genuine brand haters or an employee who works with competitors, to spread negative word-of-mouth in communities. That is why it is important to detect this emotion. This study aims to identify brand hate speech based on NLP techniques to detect consumer hate sentiment using a chatbot. We present a methodology for fine-tuning the GPT 2 language model for sentiment analysis through text classification. Experiments are conducted on datasets in three languages — Arabic, French, and English — within the context of consumer consumption. The model is retrained on labelled data to effectively identify brand hate sentiment. Furthermore, we evaluate our chatbot by conducting semi-structured interviews with diverse consumers. The experimental results demonstrate a significant improvement in sentiment analysis performance, highlighting increased accuracy when compared to other models and baseline approaches. We achieved an accuracy rate of 0.98 in the training set and 0.84 in the testing set, showcasing the utility of using GPT-2 in this context. This research contributes to the capability of managers to promptly identify brand hate speech, and proactively avert potential brand crises.

Keywords: Brand hate, NLP, Sentiments analysis, AI, GPT2

Introduction

Consumer-brand relationship plays a crucial role in the development of companies. Consumers can have positive or negative relations with brands. Recently, negative

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relationships have emerged with the advance of brand hate (Aziz & Rahman, 2022; Abbasi *et al.*, 2023; Rahimah *et al.*, 2023).

After a negative experience with the brand, haters decide to make a complaint to the brand (Kucuk, 2019a) and companies seek to manage consumers' complaints. In fact, some companies succeed at this step, while others do not, due to different factors, like customer personality (Ali *et al.*, 2020; Kucuk, 2019b), management strategies applied (Mednini & Damak Turki, 2024), and brand hate levels (Kucuk, 2019b). Sometimes the problem is not attributable to these factors but is instead rooted in genuine consumer antipathy toward the brand. In this step, some companies do not check if their customers really have negative emotions. However, the literature is still scarce regarding the recognition of hate towards brands. In fact, Kucuk (2019a) investigates that hatred can come not just from real haters but from a person who works with another competitor. It is necessary to reflect on their behaviour driven by hatred. Therefore, the company must verify the authenticity of various complaints, because some claims do not belong to angry customers but to someone who seeks to destroy brand image (Mednini & Turki, 2022; Mednini & Hmida, 2023).

Several researchers have investigated fake news via analyzing customers' sentiments (Mishra *et al.*, 2022; Meel & Vishwakarma, 2020). The progress in AI-driven technology and machine learning has simplified the production of fake news. The research of Sharma *et al.* (2023) discussed how political brand animosity and personal moral awareness can impact the willingness of voters to share political deepfake content. The development and implementation of automatic methods for fake news identification have been encouraged by the enormous volume of news that is transmitted through social media (Alonso *et al.*, 2021). The detection of hate speech from social media is based on techniques from different domains, such as Machine Learning (ML), Natural Language Processing (NLP), data mining, content extraction and retrieval, and text exploration. According to previous studies, NLP has been used by many scholars to recognise positive and negative emotions (Kudaibergenova *et al.*, 2023; Quiroz *et al.*, 2022). In fact, NLP helps brands to detect meaningless messages (Hurlock & Wilson, 2011), contaminated content (Lee *et al.*, 2011), and rumours (Castillo, 2011) that negatively impact the performance of the classification algorithm. In recent years, hate speech has increased in both offline and online communication. It is necessary to develop an automated method for identifying and removing insulting and divisive comments before their negative effects manifest (Ali *et al.*, 2022). Detecting brand hate speech plays a crucial role in mitigating criminal behaviour and safeguarding individuals' convictions. Our research goal is to detect brand hate speech using Artificial Intelligence (AI) tools, such as NLP, to support managers in fixing good digital strategies. NLP algorithms can continuously monitor and analyze vast amounts of online content, including social media, forums, and reviews. This real-

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time monitoring enables companies to promptly identify instances of brand hate and respond swiftly to mitigate potential damage (Patel & Trivedi, 2020). Therefore, our research question is: How can we detect consumers' hate through speech?

Leveraging AI helps companies thrive in the competitive digital landscape (Raghav *et al.*, 2024). In the rapidly evolving landscape of digital marketing, NLP technologies contribute to supporting digital strategies in the contemporary era characterized by big data, platforms, social media, robotics, and other technological advancements. In fact, the amalgamation of NLP with big data analytics provides marketers with unparalleled customer insights (Liu *et al.*, 2021). By analyzing vast amounts of unstructured data from various sources, including social media and customer reviews, companies can gain a nuanced understanding of consumer preferences, and sentiments. This information, in turn, informs targeted marketing strategies (Patel & Trivedi, 2020).

The remainder of this paper is structured as follows. Regarding the analysis of previous research on this issue, see Section 2. The process of the dataset, from collection to cleaning and labelling, is covered in Section 3. Our results and analysis of our findings are covered in Section 4. Section 5 presents our theoretical implications, managerial implications, and limitations and future directions.

Theoretical Background

Defining brand hate

Several studies have attempted to define the nature of brand hate (Fetscherin, 2019; Akrout & Mrad, 2023). Most fundamental emotion theorists agree that one component of emotions involves a distinct feeling that serves informational and motivational purposes, which may or may not be consciously labelled or expressed vocally (Scherer, 2022). In this regard, hate is sometimes identified in psychology and philosophy approaches as an emotion (Ekman, 1992), an attitude (Ben-Ze'ev, 2001), or a main driver behind harmful behaviour of such individuals (Rempel & Burris, 2005). In 2003, Sternberg (2003) developed a dual theory of hate connected to a mix of emotions: negation of intimacy (disgust), passion (anger, fear), and engagement (devaluation, diminution), as shown in Figure 1. First, the negation of intimacy suggests that hate involves the desire to distance oneself from the brand of hate. Second, hate is often associated with intense emotions, such as fear and anger. In a marketing context, this can translate into passionate and emotionally charged responses from customers. Third, hate can lead to cognitive processes where the targeted group or entity is devalued and diminished through contempt. In fact, consumers are actively devaluing the brand they associate with a particular brand or ideology they hate. These resentments match each dimension of the triangle's base. Even though they are independent, they interact as a whole. Kucuk (2019b) defined this main concept as "a psychological state whereby a consumer forms intense negative emotions and detachment toward brands that perform poorly and give consumers bad and painful experiences on both individual and social levels" (p. 20). Whenever the customer develops aggressive reactions toward a brand because of a negative experience, it is crucial for companies to handle the most delicate situations quickly in order to lessen the negative effects of this perception through the adoption of management strategies.

Figure 1. Triangle duplex of hate (Sternberg, 2003)

Natural language processing

Natural Language Processing (NLP) is based on linguistic theory and computational science (Al-Makhadmeh & Tolba, 2020). It draws from linguistics to understand the structure and patterns of human language and employs computational techniques to process and manipulate language data. NLP is applied to a wide array of tasks and applications (Pease *et al.*, 2023), from chatbots (Chaurasia *et al.*, 2023) and virtual assistants (Giachos *et al.*, 2023) to machine translation (Sebastian, 2023), sentiment analysis (Raheman *et al.*, 2022), information retrieval, and more.

Previous studies utilizing NLP technologies to analyze speeches have yielded insightful results across various domains. This tool has proven to be a powerful tool for extracting meaningful information from spoken or written language, enabling researchers to delve into the intricacies of communication. In political discourse analysis, NLP has been employed to uncover sentiment, identify key themes, and assess the impact of speeches on public opinion (Dunmire, 2012). In the realm of healthcare, this AI method has facilitated the extraction of valuable insights from medical speeches, contributing to advancements in clinical decision support systems and medical research (Falcetta *et al.*, 2023). Additionally, in business and marketing, this technique has been instrumental in sentiment analysis of customer feedback and market trends, aiding companies in making informed decisions (Patel *et al.*, 2023).

NLP is a dynamic and evolving field with a wide range of practical applications across industries such as healthcare, finance, marketing, and customer service. It is important to note that NLP continues to advance and expand its capabilities, making it a fascinating and influential area of research and development in the world of Artificial Intelligence.

Detecting brand hate via NLP

Table 1. Overview of literature review on NLP

Author and Date	Research objective and Context	Feeling	Language	Dataset
Ayo *et al.* (2020)	Look at how consumers use Twitter's emojis, text, and hashtags to express their hate.	Hate	Arabic, English, Danish	Not available
Abro *et al.* (2020)	This study aims to make a comparison to study the different tools applied for hate speech (message) in the context of social networks.	Hate	English	Available at CrowdFlower (contains 14509 tweets)
Oriola & Kotzé (2020)	This work explains the automatic learning techniques to find offensive and hateful language in South African tweets.	Hate	African, English, Sesotho, Isizulu	Available at: https://digitalinspiration.com/product/twitter-archiver
Roy *et al.* (2020)	This article discusses hate speech issues on Twitter using Convoluted Neural Networks (CNNs).	Hate	English	Available at: https://www.kaggle.com/vkrahul/twitter-hate-speech?select=train_E6o V3lV.csv
Mullah & Zainon (2021)	The purpose of this article is to describe automatic learning algorithms and approaches (ML) for detecting hate speech on social media.	Hate	English	Not available
Ali *et al.* (2022)	This study utilized the transfer learning technique for detection of hate speech on Twitter.	Hate	Farsi, Urdu, Arabic	Not available
Rodriguez *et al.* (2022)	The purpose of this study is to identify and incorporate unstructured data from Facebook hate speech using sentiment and emotion analysis.	Hate	English	Not available

A multitude of approaches have been employed to forecast instances of hate speech on social media platforms. By leveraging the power of Natural Language Processing and Artificial

http://doi.org/10.18080/jtde.v12n1.859

Intelligence (Parihar *et al.*, 2021), semantic text and hateful content can be effectively monitored.

Several research studies have been conducted to automatically detect these undesirable messages, among others, on social media platforms (Mullah & Zainon, 2021). Social media, along with other online platforms, play a significant role in the reproduction and dissemination of hate content, eventually leading to hate crimes. Table 1 provides an overview of the literature review on Natural Language Processing.

Cyberbullying, toxic language or comment and hate speech are typical examples of abusive language that researchers have increasingly focused on in recent decades, due to their negative impacts on our societies. Table 2 discusses the differences in composition of hate speech.

Table 2. Composition of hate speech

Concept	**Definition**	**Distinction between hate and other concepts**
Hate	Expression of hostility without any reason for it (Tarasova, 2016)	Hate speech is hate which focuses on stereotypes and not general.
Cyberbullying	Using information and communication technologies (ICT) to repeatedly and intentionally harm, harass, hurt and/or embarrass a target. (Peter & Petermann, 2018, p. 359)	Hate speech is more general and does not focus on a specific person.
Abusive language	Used to refer to hurtful language, including hate speech, derogatory language and also profanity (Founta *et al.*, 2018)	Hate speech is a kind of abusive language.
Profanity	Offensive or obscene word or expression (Del Vigna *et al.*, 2017).	Hate speech can use profanity but not inevitably.
Toxic language or comment	Toxic language is a rude, disrespectful or irrational comment that is likely to make a person leave a discussion (Jigsaw, 2017)	Not all toxic comments include hate speech. In contrast, some hate speech can make people discuss more.
Extremism	The extent of support for the use of violence against outgroup members on the basis of their … affiliation … to achieve … [religious, political, or social] objectives. (Sharma, 2016)	Extremist discourses frequently used hate speech. In contrast, these discourses focused on other topics as well, like new member recruitment, social media demonization of the in-group and persuasion (McNamee *et al.*, 2010).
Radicalization	The process by which an individual, group, or mass of people undergo a transformation from participating in the political process via legal means to the use or support of violence for political purposes (radicalism).	Radical discursions like extremism used hate speech. However, in radical discursions, topics like war, religion and negative emotions are common (Agarwal, 2015).

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Research Methodology

Our research goal is to recognize hate sentiments via Natural Language Processing. The annotators were asked to assign one class to each comment, where classes span the following levels of hate: No brand hate; and brand hate.

Brand hate speech detection method

Text classification stands as a pivotal task in NLP, playing a crucial role in the automated organization and analysis of extensive textual datasets (Noubigh *et al.*, 2021). Transformer-based models, known for their capacity to capture long-range dependencies and contextual information, have demonstrated state-of-the-art performance in these NLP tasks (Islam *et al.*, 2023). Generative Pre-Trained Transformer (GPT) models exclusively leverage the decoder block of transformers, significantly advancing the progress of transformers in natural language processing. GPT adopts a semi-supervised approach to language comprehension, encompassing unsupervised pre-training and supervised fine-tuning methods (Radford *et al.*, 2018). Following the success of the GPT model, GPT-2 was introduced in 2019, boasting 1.5 billion parameters and further improving pre-trained transformer versions (Radford *et al.*, 2019). Subsequently, GPT-3, the largest pre-trained version with a staggering 175 billion parameters, was unveiled in 2020.

In this work, we opted to utilize GPT-2 and not GPT-3 due to its restricted accessibility through an API. The weights and parameters of GPT-3 are not openly available to researchers, limiting our ability to customize and fine-tune the model according to our specific requirements. Seeking an open-source alternative that allows greater flexibility, we turned to GPT-2.

Text classification finds application in several fields such as spam filtering, sentiment analysis, customer support automation, and news categorization (Zhao *et al.*, 2023). Recently, the industry has seen a surge in utilizing deep learning language models, notably Transformers, for large-scale text classification (Bharathi Mohan *et al.*, 2023). GPT-2, a member of the Transformer model family, has gained recognition for its capabilities in this realm (Bahani *et al.*, 2023).

In this work, we focus on the process of training and deploying a fine-tuned GPT-2 model for text classification tasks. The brand hate speech detection method used is described in this section and illustrated in Figure 2. In the initial stage, we performed preprocessing on the datasets, followed by their division into three sets: training, validation, and testing. The subsequent step involves fine-tuning, wherein the training and validation sets are utilized for model training, while the test set is employed to evaluate the model's performance. The outcome is a binary decision indicating whether the text contains hate speech or not.

http://doi.org/10.18080/jtde.v12n1.859

Subsequently, this trained model is integrated into our developed chatbot to determine whether a given comment contains hate speech or not. In the following sections, we provide more detailed insights into each of these steps.

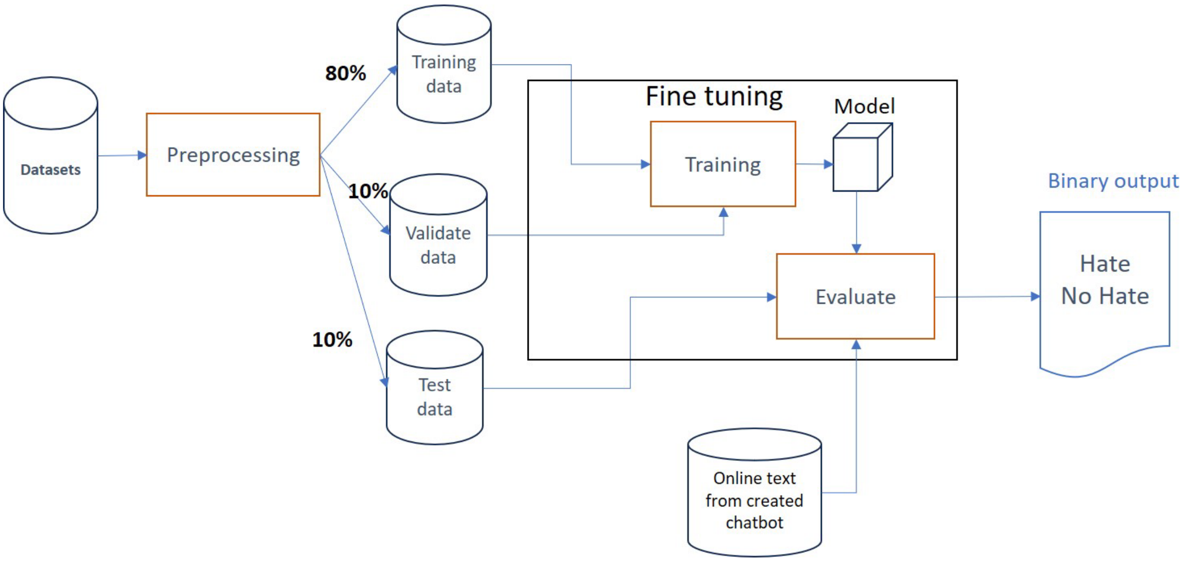

Figure 2. Steps of brand hate speech detection

Datasets' collection and preprocessing

In this section, we introduce the datasets utilized in our research, spanning multiple languages and catering to different dimensions of hate speech.

We used two datasets for Tunisian dialect in this work. The first is developed by the "Developer Student Clubs Tunisia" from Tunisian apps on Google Play (Antit *et al.*, 2022). The primary goal of this endeavour is to categorize reviews from popular Tunisian applications on the Google Play Store, determining whether they convey positive, negative, or neutral sentiments. The second dataset is collected by the authors from Tunisian communities on Facebook and is focused on exploring consumer hate towards brands. This unique dataset is particularly distinctive, as it captures the sentiments of consumers using the Tunisian dialect, reflecting the specific linguistic and cultural context of Tunisia.

The CONAN dataset (Chung *et al.*, 2019) is a versatile resource, meticulously designed to facilitate comprehensive studies and approaches to hate speech detection across language barriers. Multilingual in nature, this dataset encompasses English, French, and Italian, allowing researchers to explore hate speech dynamics in distinct linguistic contexts. The hate speech/counter-narrative pairs in the CONAN dataset are obtained through specialized collaboration with non-governmental organizations (NGOs) from the United Kingdom, France, and Italy. Figure 3 provides examples from the datasets. The collected data comprise 78,112 comments across three languages, distributed into three sets: 62,489 (80%) for training, 7,811 (10%) for validation, and 7,812 (10%) for testing.

	text	category
0	جوميا موقع ثقه وأسعار جميلة اشتريت منه حاجات ك...	1
1	روووووووووووووووووووعة	1
2	Bien mais on ne retrouve plus certains produit...	0
3	Cest génial on trouve à peu près tout là-bas s...	1
4	jai bcp aimé jumia	1
...	...	...
78107	Just returned from the Phoenix area and so my ...	1
78108	Absolutely sensational food. We had the eveni...	1
78109	How can I not show yelp love for the original ...	1
78110	I eat here frequently as I stay at the adjoini...	1
78111	My office moved to the area so I was driving a...	1

78112 rows × 2 columns

Figure 3. Example extracted from the datasets

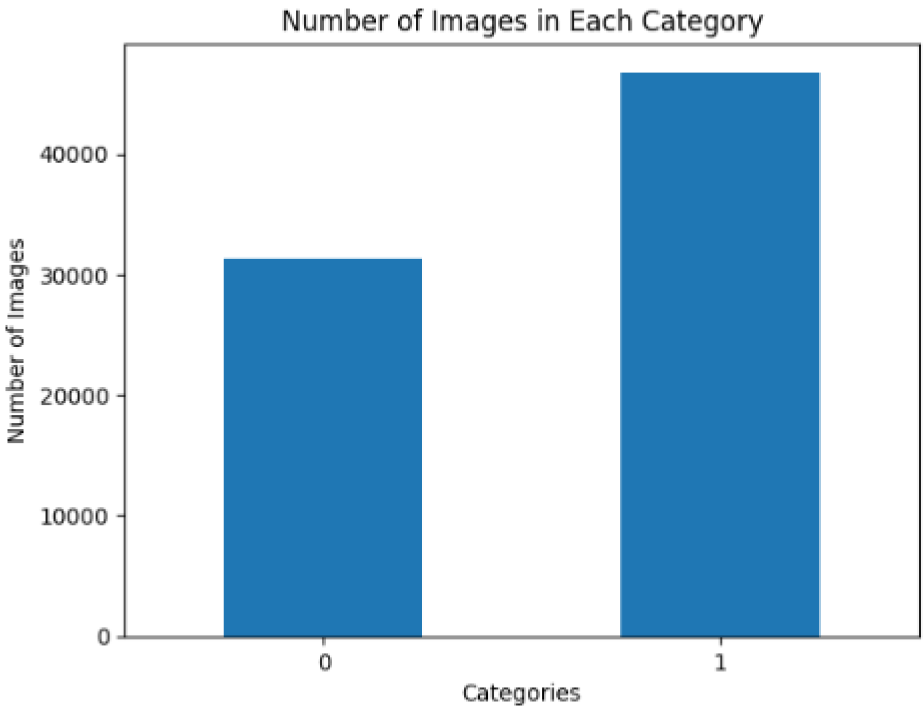

Figure 4. Dataset split into training and test

To enhance hate speech identification, the proposed system uses these key processes:

- Data cleaning involves removing unwanted characters and symbols from Twitter data, eliminating unnecessary content, such as URLs, tags, and hashtags, to refine the text for analysis.
- Tokenization, facilitated by OpenNLP, dissects sentences into smaller parts to analyze their components, including the identification of parts of speech (nouns, verbs, adjectives, etc.) to discern negative connotations.
- The system generates a negation vector using a lookup table, assigning negative words a value of 0 while remaining words receive a +1, aiding in the determination of the

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sentiment of the text. In fact, Figure 4 illustrates the distribution of each category within our methodology.

Fine-tuning: training step

Fine-tuning is the subsequent process of customizing a pretrained neural network model to a new task or dataset. This entails further training the model specifically on the target task or dataset. In the context of GPT, fine-tuning involves refining the parameters of the pre-trained model to enhance its performance on a designated downstream task, such as text classification or text generation (Bangura *et al.*, 2023).

GPT-2, a transformer-based architecture, employs a series of steps to extract meaningful representations from the input text, enabling accurate classification (Yenduri *et al.*, 2023). The process begins with tokenization, where the input text is segmented into tokens. Each token corresponds to a specific word or subword and is mapped to a unique identifier recognized by the model. Following tokenization, each token undergoes an embedding process. GPT-2's embedding layer converts tokens into fixed-size vectors. These embeddings encode rich semantic and contextual information of the tokens, capturing their meaning within the given context. Positional encodings are then introduced to these token embeddings. These positional encodings provide crucial information regarding the sequential order of the tokens within the text sequence, enabling GPT-2 to understand the relative positions of words or subwords in the input.

GPT-2 is based on self-attention mechanisms that allow the model to comprehend the relationships and dependencies between words across the entire sequence (Islam *et al.*, 2023). This mechanism enables the model to capture contextual nuances and long-range dependencies within the text.

For text classification purposes, the final hidden states from the GPT-2 model serve as the extracted features. Typically, the output from the last layer or a specific pooling layer contains rich representations of the entire input sequence. These representations encapsulate comprehensive information about the text and are utilized as features for the subsequent classification task.

The extracted features are then fed into a classification head, such as a linear layer or a multi-layer neural network, to perform the specific text classification. During training, these features are optimized through fine-tuning the model's parameters with labelled data, aiming to minimize a defined loss function and enhance the model's classification performance.

Experimental setup

We conducted interviews with consumers who had negative and positive experiences with brands. In total, 14 semi-structured interviews were conducted to test our chatbot with Tunisian Consumers. The interviews, which lasted between 10 and 15 minutes, involved discussions with a chatbot. The sense-making perspective served as the foundation for two major research topics that aimed to: (1) understand the causes of the customer's unpleasant brand experience; and (2) examine how the company handles customer complaints. We developed a chatbot that determines whether one of our customers is using hate speech. The chatbot we created helps us recognize the precise percentage of hate speech directed towards brands in all the interviews discussed in the conversation. Some discussions show a high level of hate, while others exhibit a lower percentage of hate.

Results and Discussion

In this section, we present the results obtained from the analysis of the utilized data, employing accuracy, precision, recall and F1-score as metrics to assess performance. To define those metrics, we establish four values as follows:

- True positives (TP): The number of samples that were correctly predicted as positive.
- True negatives (TN): The number of samples that were correctly predicted as negative.
- False positives (FP): The number of samples that were incorrectly predicted as positive.
- False negatives (FN): The number of samples that were incorrectly predicted as negative.

The accuracy score is a metric defined as the ratio of true positives and true negatives to the total number of positive and negative observations. In essence, it provides insight into how frequently we can expect our machine learning model to accurately predict outcomes from the entire set of predictions made. The formula for the accuracy score is given in (1):

$$Accuracy = (TP + TN) \div Total\ observations \tag{1}$$

Precision tells us how many of the correctly predicted cases actually turned out to be positive. This would determine whether our model is reliable or not. Here is how to calculate Precision:

$$Precision = TP \div (TP + FP) \tag{2}$$

Recall tells us how many of the actual positive cases we were able to predict correctly with our model. In practice, when we try to increase the precision of our model, the recall goes down, and vice-versa. Here is how we can calculate Recall:

$$Recall = TP \div (TP + FN) \tag{3}$$

F1-score is a harmonic mean of Precision and Recall, and so it gives a combined idea about these two metrics. It is maximum when Precision is equal to Recall. The F1-score captures both the trends in a single value:

$$F1\text{-}score = 2 \div \left((1 \div Recall) + (1 \div Precision)\right) \quad (4)$$

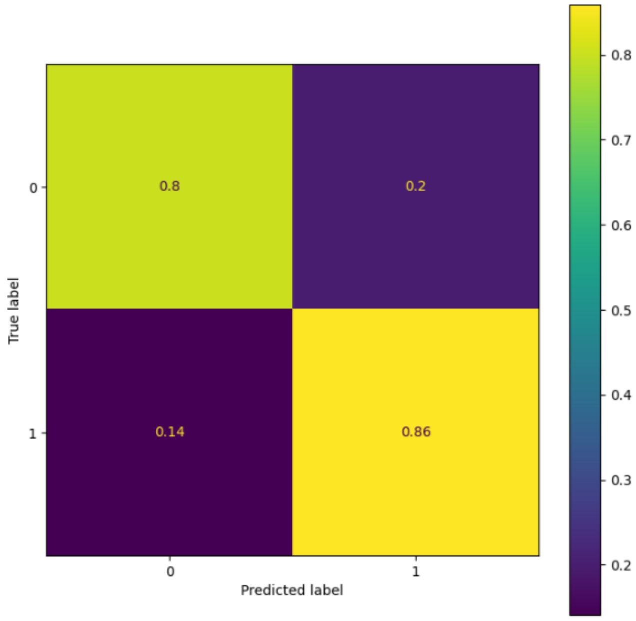

Figure 5. Testing confusion matrix

The confusion matrix provides a comprehensive overview of the model's accuracy by depicting the counts of true positives, true negatives, false positives, and false negatives. In a confusion matrix, each cell represents the count of instances for a combination of actual and predicted classes. The diagonal elements represent correct predictions, while off-diagonal elements represent errors. Analyzing the confusion matrix facilitates the identification of misclassifications, contributing to the enhancement of predictive accuracy. For binary classification problems, such as the one depicted in Figure 5, a 2 x 2 matrix is employed, featuring four values. Figure 5 illustrates the testing confusion matrix, portraying the model's performance for each label. To visually represent the performance of the model, colours may be used to highlight different levels of correctness or errors. In Figure 5, the colour gradient is used to show higher values in yellow colours and lower values in dark blue colours. This colour representation makes it easier to identify patterns and areas where the model may need improvement. Notably, for the "NO Hate" label, the recall of 0.8 signifies that the model accurately identified 80% of instances belonging to the "NO Hate" category. Conversely, the precision for the "Hate" label is reported as 0.86, indicating that 86% of instances classified as "Hate" were correct. The overall accuracy of the model is documented at 0.83, denoting that it correctly classified 83% of instances.

http://doi.org/10.18080/jtde.v12n1.859

Table 3 shows the accuracy, precision, recall and F1-score values (weighted averages for precision, recall and F1-score) for all classes on the testing set of the dataset.

Table 3. Final results in testing set

Data	Accuracy	Precision (Weighted-Average)	Recall (Weighted-Average)	F1-score (Weighted-Average)
Testing set	84	85	88	83

The final results on the Testing set reveal a commendable performance of the classification model. With an accuracy of 84%, the model demonstrated a strong capability in correctly classifying instances. The Precision of 85% emphasizes the accuracy of positive predictions, indicating that 85% of the instances predicted as positive were indeed true positives. The Recall at 88% signifies the model's effectiveness in capturing a substantial portion of actual positive instances. The F1-score of 83% strikes a balance between precision and recall, further reinforcing the model's robustness. Overall, these metrics collectively underscore the model's reliability and efficiency in handling the Testing set, suggesting its potential suitability for the intended classification task.

Table 4. Comparative performance with other models

Model	Accuracy	Language	Application
TunRoBERTa (Antit *et al.*, 2022)	79.1	Arabic dialect	Sentiment analysis
TunRoBERTa+CNN (Antit *et al.*, 2022)	80.6	Arabic dialect	Sentiment analysis
CNN (Madichetty & Sridevi, 2020)	72.98	English	Crisis-related data during a disaster
MLP-CNN (Madichetty & Sridevi, 2020)	73.19	English	Crisis-related data during a disaster
Dense classifier model with ELMo embeddings (Madichetty & Sridevi, 2020)	77.57	English	Crisis-related data during a disaster.
Proposed method (GPT2)	84.01	Multi-language (French, English, Tunisian dialect)	Sentiment analysis

Table 4 provides a comprehensive overview of several language models, shedding light on their respective accuracies and applications across different languages. The TunRoBERTa models (Antit *et al.* 2022) showcase their prowess in Arabic sentiment analysis by achieving an accuracy of 79.1. The subsequent TunRoBERTa+CNN model improves upon this, achieving a higher accuracy of 80.6. Shifting the focus to English language applications, Table 4 includes results from various models targeting crisis-related data during disasters. The basic CNN

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model achieves an accuracy of 72.98, while the MLP-CNN model slightly surpasses it with an accuracy of 73.19. The inclusion of a dense classifier model with ELMo embeddings significantly raises the accuracy to 77.57.

The proposed method using GPT2 achieves an accuracy of 84.01 in sentiment analysis across multiple languages, including French, English, and Tunisian dialect. This underscores the versatility of GPT2, demonstrating its capability to handle sentiment analysis tasks across diverse linguistic contexts.

In essence, Table 4 illustrates the evolving landscape of natural language processing models, showcasing advancements in both architecture design and application-specific fine-tuning. The varying accuracies across models and languages emphasize the importance of tailoring approaches to the specific linguistic and contextual characteristics of the target task, paving the way for more effective and nuanced natural language understanding.

The comparative table underscores the pivotal role of fine-tuning in optimizing language models for specific tasks. In the realm of sentiment analysis for Arabic dialects, the proposed method utilizing GPT2 demonstrates the versatility of fine-tuning across multiple languages, emphasizing its value in adapting models to diverse linguistic contexts for sentiment analysis. Overall, these findings underscore fine-tuning's instrumental role in enhancing the performance of language models across various applications and languages.

Furthermore, in the Appendix, we provide illustrative examples of text inputs in various languages that were tested within the developed chatbot to distinguish expressions of both hate and no hate sentiments towards a brand.

According to Sternberg (2003), hate is a complex emotion that encompasses four primary components: fear, contempt, disgust, and anger. The findings underscore the capability of this tool as proficient in recognizing various consumer negative emotions. By dissecting hate into its constituent emotional elements, NLP not only enhances our understanding of the nuanced aspects of this complex sentiment but also offers a valuable means to identify and address distinct negative emotional states within consumer expressions (Ma *et al.*, 2023).

While the content analyzed by computer programs relies on the researcher's subjective choices regarding variables, statistical NLP empowers researchers to observe phenomena and derive valuable insights from vast amounts of text — an intricate undertaking in the era of electronic communication and big data (Zimand-Sheiner *et al.*, 2021). Our paper encourages managers in managing online communities, such as improving consumer engagement towards brand, competitor analysis, and personalized customer interactions in different contexts. In fact, in the advertising context, the result of Sun *et al.* (2022) has highlighted the importance of NLP

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aids for advertisers in gathering consumer data from various origins and extracting valuable insights in real time, in order to understand consumer opinions towards brands. Furthermore, the adoption of customer sentiment analysis based on online reviews is recognized as a trend in numerous real-life applications, encompassing behaviour analysis, decision-making, and obtaining valuable insights for organizational advancement (Jain *et al.*, 2021). In fact, our result helps in detecting crises to fix good management strategies for companies via detecting sentiment analysis. In accordance with the findings from the study of Kaur & Sharma (2023), the results affirmed the significance of creating a consumer review summarization model utilizing NLP techniques.

Conclusion

Our research represents a significant advancement in the field of marketing as it pioneers the integration of AI in recognizing brand hate expressed through speech using NLP. Numerous academic research corroborates the serious implications caused by the widespread propagation of hate speech. It leads to strange psychological issues in addition to crimes (Chaudhary *et al.*, 2021). Contributing to the theory duplex of hate, the current study helps academics and practitioners better understand the dynamics of consumer brand relationships in the digital age. According to our work, researchers need to use AI methods to identify haters. To the best of our knowledge, our work stands among the pioneering studies in the analysis of hate speech using GPT2. According to our results, we obtained promising performance with a training accuracy of 0.98, outperforming the BERT model using the dataset of Antit *et al.* (2022). This highlights the promising potential of GPT-2 in sentiment analysis, signalling its capability to surpass established models. These findings underscore the importance of considering GPT-2 in sentiment analysis tasks, which could lead to enhanced insights and more accurate predictions in various domains, such as marketing. NLP allows researchers to collect and analyze vast amounts of unstructured text data from various online sources like social-media product reviews.

Our findings yield numerous managerial implications for businesses. First, our research enhances the authenticity of consumer complaints, providing companies with valuable insights to integrate AI into their management processes as a means to address and alleviate customer dissatisfaction effectively. Second, brand hate speech can proliferate rapidly online and harm a company's image and credibility, ultimately impacting sales and revenue. Recognizing and addressing brand hate helps companies effectively manage these risks. In fact, NLP can help recognize and quantify expressions of consumer dissatisfaction, frustration, hate, fear, or anger towards brands in online conversations. This enables the identification of specific issues or pain points. Third, another contribution of our study is the recognition that

http://doi.org/10.18080/jtde.v12n1.859

brand hate speech can also significantly impact the morale of employees working for the company. Fourth, our work can be a valuable tool in crisis management. Companies can use NLP to identify emerging issues and respond rapidly, potentially preventing a small problem from escalating into a major crisis. After that, companies can tailor their marketing strategies based on the sentiment and authenticity of their audience. Positive engagement with authentic consumers can be rewarded, while negative engagement can trigger appropriate responses.

Detecting brand hate through speech raises ethical questions surrounding the responsible use of AI in detecting emotions. Future research could spark discussions on the ethical boundaries of employing advanced technologies in consumer behaviour studies. Furthermore, every person has a unique way of expressing their emotions, such as utilizing voice-over speech, as supported by previous works in this field (Amari *et al.*, 2022). Companies can actually identify haters using a variety of measures, including body language, facial expressions, and customer voice in further research.

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Appendix

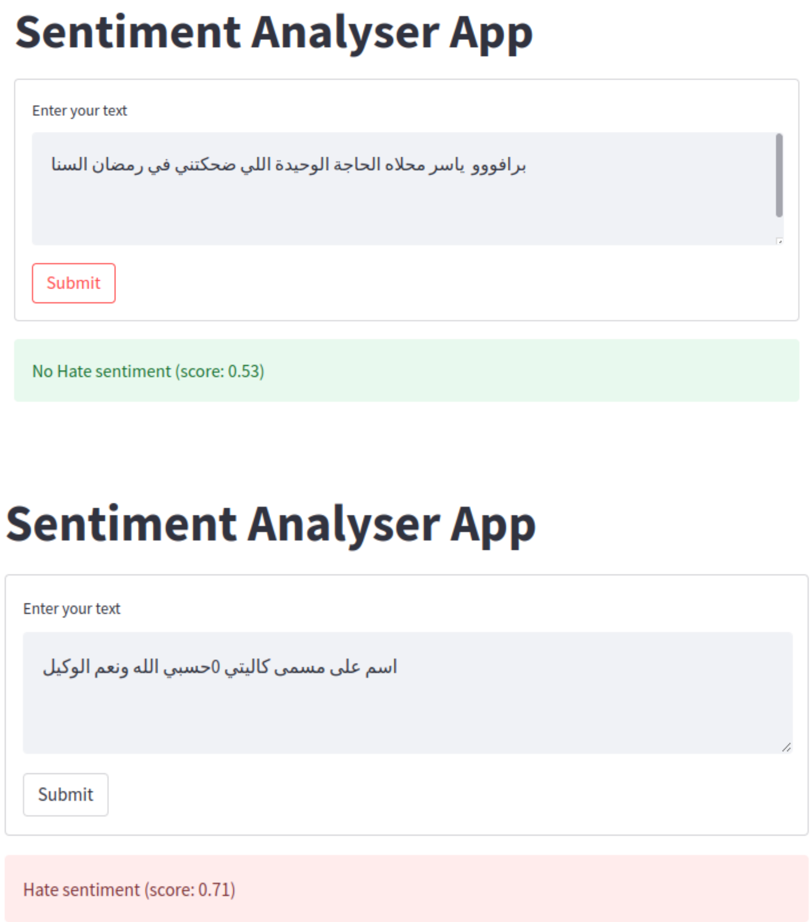

Figure A1. Results of brand hate speech in Arabic language

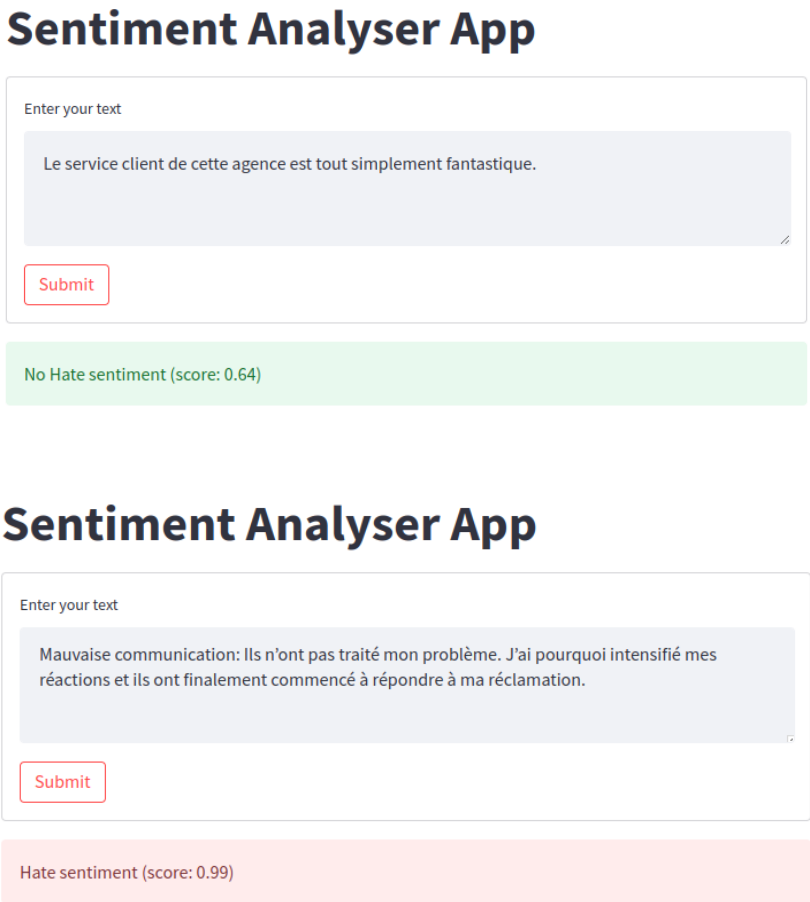

Figure A2. Results of brand hate speech in French language

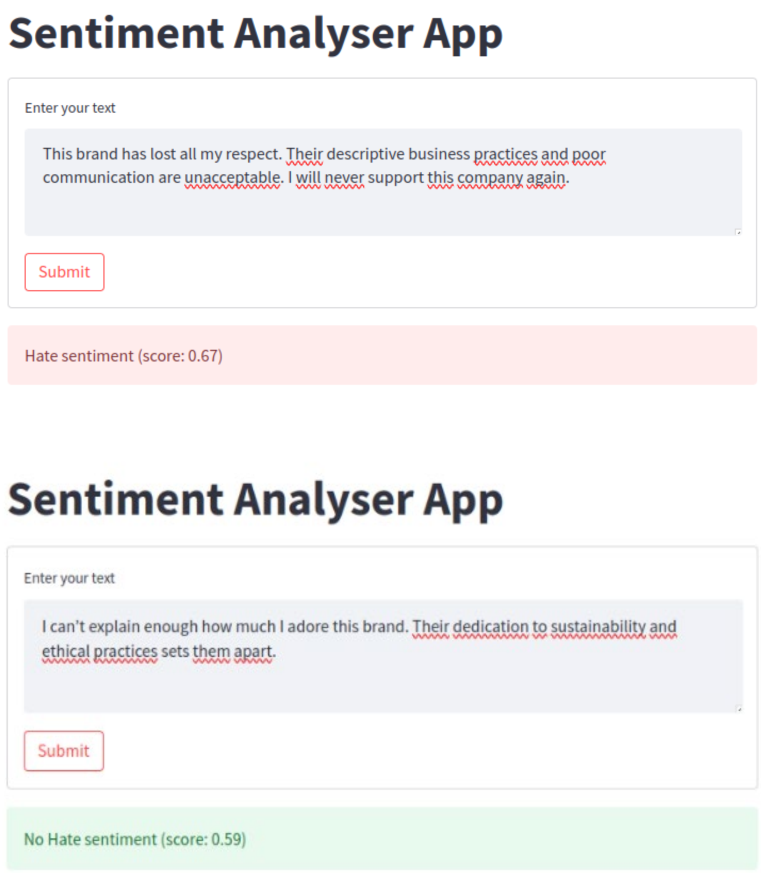

Figure A3 Results of brand hate speech in English language

Clustering Social Media Data for Marketing Strategies

Literature Review Using Topic Modelling Techniques

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Abstract: With the rise of social media platforms for marketing purposes, the central dilemma for researchers and policymakers lies in choosing effective data analysis tools to improve marketing decisions. In the academic literature, numerous articles have discussed clustering techniques for analysing social media data, from a perspective of data mining or social media marketing. However, few studies have attempted to synthesise results obtained from both perspectives. This research aims to (1) offer a structured overview of existing literature on clustering methods for marketing strategies and (2) compare three topic modelling techniques applied to extract the main topics evoked in the corpus of papers. Indeed, topic modelling emerges as a valuable tool for extracting relevant information from big data in general and more specifically from extensive scientific papers. Based on a thematic analysis, the extracted topics were classified according to the following categories: fields, marketing strategies and technologies. Results prove that latent Dirichlet allocation (LDA) is the most effective technique in this context. Furthermore, this study provides an overview of clustering techniques and technologies used for marketing strategies in studied fields. These findings help researchers and practitioners to select the best techniques and technologies for extracting marketing knowledge from big data.

Keywords: social media data analytics, marketing strategies, technology, clustering, topic modelling

Introduction

The surge in big data analytics, fuelled by internet and Web 2.0 technologies, is reshaping research landscapes, especially with the prevalence of social media applications (Ghani *et al.*, 2018). The complex and unstructured nature of these datasets poses challenges, and effective strategies are needed to extract actionable insights for improved marketing decisions. Previous research efforts, including data mining and machine learning, have turned to clustering techniques as popular approaches for analysing social media data in marketing contexts (Benslama & Jallouli, 2020; 2022).

However, amidst this active research, there exists a noticeable gap in the literature, with scattered publications across various fields. This research aims to systematically address this gap by (1) offering a structured overview of existing literature on clustering methods and their application to marketing strategies, and (2) enhancing the comprehension of novel techniques arising from digital transformation context, namely topic modelling that emerges as a valuable tool for extracting relevant information from big data in general and more particularly from extensive scientific papers. The comparison of topic modelling techniques' performance would guide researchers and analysts of big data for a better use of the adequate technique based on the objectives and available datasets.

This paper employs several topic modelling tools to automatically extract the most cited topics from a corpus of marketing articles dealing with clustering social media data and to classify the resulting topics into relevant categories. The following method is deployed: first, this study uses three topic modelling techniques to analyse 60 marketing papers; second, this research performs both an objective evaluation using machine learning metrics and a subjective evaluation using the judgement of marketing experts, to compare the techniques and select the most appropriate one for this context; third, this paper classifies the resulting topics into three related categories, namely fields, marketing strategies and technologies. This classification helps to map the main topics studied by category and suggests orientation for future research.

The first section of this paper provides an overview of the evolution of social media, emphasising big data generation and the application of social media data analytics for marketing strategies, along with insights into clustering techniques for marketing strategies. The second section delineates the methodology employed in the analysis of a collection of scientific papers within the domain of clustering social media data and marketing. And the third section introduces the topic modelling process and techniques. In the fourth section, we delve into the study's findings, encompassing the determination of the optimal number of topics, the steps taken to evaluate the results, a comparative analysis with prior research, and

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the mapping of these identified topics to specific categories. This mapping serves to enhance the visualisation of the most frequently referenced topics, categorised by fields, marketing strategies and technologies. This study ends with a summary of the main findings and some future research directions.

Clustering Social Media Data for Marketing Strategies

In the realm of marketing, social media is considered as fundamentally different from other digital media and has the potential to revolutionise marketing. Studies have demonstrated that active participation in a company's social media activities can positively influence its profitability (Keegan & Rowley, 2017). Human interactions on social media platforms now serve as a rich source of unstructured, detailed and large-scale digital data. This substantial growth in social media's daily use has led to the rapid accumulation of diverse and unstructured data, exemplifying key features of big data. With over a trillion users actively generating voluminous and unstructured data every second, social media has emerged as the primary source of big data (Matilda, 2017).

Prominent social networking sites that generate substantial data encompass Facebook, Twitter, Instagram, LinkedIn, blogs, wikis, YouTube and WhatsApp. For example, in 2021, within 60 seconds, 95,000 stories were shared on Instagram, 500 hours of video content were uploaded to YouTube, and nearly 70 million private messages were exchanged via Facebook Messenger and WhatsApp (Jenik, 2021). Big data originating from social media proliferates at an exponential rate and is distinguished by its heterogeneity. Big data exists in various types, such as structured, unstructured and semi-structured data. This encompasses content such as videos, audio, documents, images, comments, likes, tags, tweets and more. To handle and process this diverse data, we need machine-driven analysis. Semi-structured data, which includes elements like graphics and text, adds complexity to the analysis (Rawat & Yadav, 2021; Banu & Nivedita, 2023).

Nonetheless, a universal definition for big data remains elusive, as some definitions focus on what big data represents, while others delve into its functionality. While size is the most obvious characteristic associated with big data, other dimensions have emerged over time. Numerous definitions of big data were gathered from research, but they can be simplified into two main definitions. The first definition interprets big data as large datasets collected from various sources. The second definition emphasises the rapid increase in the quantity and quality of available and relevant data. In this context, social media data is commonly referred to as 'Social Media Big Data' (Lynn *et al.*, 2015). To effectively handle social media data, it is crucial to grasp how researchers have tackled big data analysis. Consequently, various recent

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studies have emerged with the aim of identifying the distinct analytical features of social media data that differ from big data.

Social media data analytics for marketing strategies

Companies worldwide are increasingly striving to gain a comprehensive and clearer comprehension of big data (Morabito *et al.*, 2015). Acquiring data is just the starting point; what managers truly desire is to comprehend its significance and utilise it for informed decision-making. For marketers, the challenge is to effectively analyse this extensive data to guide marketing decisions, generate value, and uncover indispensable and valuable insights. Big data analytics involves the process of using algorithms to study datasets, finding hidden patterns, relationships and useful information. Big data analytics provides a method for finding value in large amounts of information, opening up new market possibilities, and enhancing customer loyalty (Zakir *et al.*, 2015). As a result, analytics have become a significant force in research and technology. Decision-makers are increasingly interested in learning from past data to gain a competitive advantage (Elgendy & Elragal, 2014). Previous work in the field of marketing introduced how social media helps organisations gather customer feedback on their products, which can then be leveraged to make informed decisions and create value for their businesses (Katal *et al.*, 2013; Wu *et al.*, 2013). Jimenez-Marquez *et al.* (2019) introduced a big data framework to enhance decision-making within businesses through analysing social media content. They also conducted a case study that focused on assessing internet users' opinions regarding tourism services, specifically hotels and resorts. Yang *et al.* (2022) introduced the Business Decision Making System (BDMS) as a framework for leveraging social media data analytics (SMDA) to enhance business operations.

Campbell *et al.* (2020) outlined that marketing strategies mainly fall into five categories: targeting and positioning strategy; product, service and brand strategy; pricing strategy; channel and logistics strategy; and communications and influence strategy. Using social media data analysis to improve marketing strategies is a big challenge for researchers. In the past 10 years, many studies have used social media data analysis to achieve marketing goals, resulting in more research in this area. He *et al.* (2019) effectively harnessed the potential of social media big data analysis to unearth invaluable customer insights and to strengthen marketing strategies. Similarly, Wang *et al.* (2021) made use of Krippendorff's Content Analysis to assess marketing strategies via social media, with a specific focus on the scrutiny of two Instagram accounts associated with Grab, a prominent online transportation service provider in Southeast Asia. Additionally, Marine-Roig & Clave (2015) applied data mining techniques to analyse data extracted from travel websites, aimed at improving branding and positioning strategies within the tourism and destination sector. Many articles focus on SMDA for specific marketing strategies, but there is a lack of research covering its impact on all marketing approaches and the related analytical methods. Benslama & Jallouli (2022) addressed this gap through an extensive literature review.

Clustering techniques for marketing strategies

For effective analysis of social media big data and to ensure consistent results, the choice of appropriate analytical methods is crucial. Many studies have revealed the growing focus on big data analysis techniques in the context of social media data (Kowalczyk & Buxmann, 2015; Kim & Hastak, 2018; Stieglitz *et al.*, 2018). These investigations have consistently pointed out that machine learning methods play a central role in the analysis of extensive social media data (Cambria *et al.*, 2013). Commonly utilised techniques encompass classification (Reuter & Cimiano, 2012), clustering (Lim *et al.*, 2017) and deep learning (Jansson and Liu, 2017). Kirilenko *et al.* (2019) approached the subject from a unique perspective, concentrating on the clustering challenges of tourist attractions based on the interests of travellers. To accomplish this task, they harnessed data from the TripAdvisor website and employed network analysis, spatial analysis and geo-visualisations. The result was the identification of three distinct clusters in each domestic market, categorised as Entertainment, Heritage and Nature. Furthermore, Benslama & Jallouli (2020) carried out a comprehensive literature review, delving into the intricate world of social media data clustering techniques and their applications in shaping marketing decisions. These diverse endeavours highlight the expansive utility and adaptability of SMDA across various industry domains.

Clustering is a machine learning task where data or data points without labels are grouped together based on their similarities to form clusters with shared characteristics. It serves two main purposes: reducing the complexity of data, often as a preliminary step, and identifying important patterns within datasets. These techniques generally involve iterative optimisation methods, but they can be computationally demanding and expensive, especially when dealing with complex, high-dimensional data (Saeed *et al.*, 2020). Clustering approaches are broadly classified into four categories: density-based, partition-based, hierarchical and model-based (Bataineh & Alzah, 2023). The application of clustering techniques played a pivotal role in discerning patterns and revealing intriguing correlations within these extensive datasets. Madhuri *et al.* (2014) compared and implemented three algorithms: incremental K-means, modified K-modes, and K-prototypes across various real-world datasets. Their findings revealed that incremental K-means outperforms simple K-means for numeric data, modified K-modes excels over K-modes for categorical data, and K-prototypes proves beneficial for clustering mixed data (categorical data and numeric data). Additionally, the K-prototypes paradigm combines aspects of both K-means and K-modes. Consequently, all of these algorithms lead to a reduction in the cost function value. Jayanthi and Priya (2018) used hierarchical, K-means and fuzzy C-means clustering techniques to categorise scientific articles from various domains based on keyword lists. In our research within this field, our focus is on clustering techniques for analysing social media data.

Research Methodology

The objective of this research is to review the literature on clustering social media data in the context of marketing and to compare the three topic modelling techniques – latent semantic analysis (LSA), latent Dirichlet allocation (LDA) and correlated topic model (CTM) – as techniques used for this purpose. Topic modelling techniques are an effective tool for automatically analysing and extracting knowledge from article collections. Ultimately, our goal is to automatically extract the maximum of topics from the corpus, and to recommend the most effective technique for future research in this area.

The division of the obtained corpus was carried out based on a thematic analysis. Indeed, the extracted topics were classified according to each thematic idea referring to one or more of the following categories: fields, marketing strategies and technologies. This step was done manually without using a software. The findings from this study provide a valuable overview framework for marketing researchers and data analysts.

The methodology adopted in this work is based on six steps. The first step involves the collection of marketing scientific papers (the corpus). In our search for these articles, we used specific keywords: 'marketing', 'clustering', and 'social media data'. The second step consists of the pre-processing of the corpus. The third step is related to the corpus transformation in document-term matrix D(d,w) where d represents documents of the corpus and w represents words (unigrams and bigrams). The fourth step is the application of topic modelling techniques LSA, LDA and CTM on the corpus. Only the 'title', 'abstract' and 'keywords' parts of the corpus are analysed. When we used topic modelling to analyse the articles, each method made its own topics. These topics are groups of words that go together. To make it easier to understand, we sorted these topics into categories. Furthermore, by using the keyword 'clustering,' we encountered categories related to technology that encompassed various technologies beyond clustering techniques.

The fifth step is the objective evaluation and finally, the sixth step is the subjective evaluation. Figure 1 presents this process.

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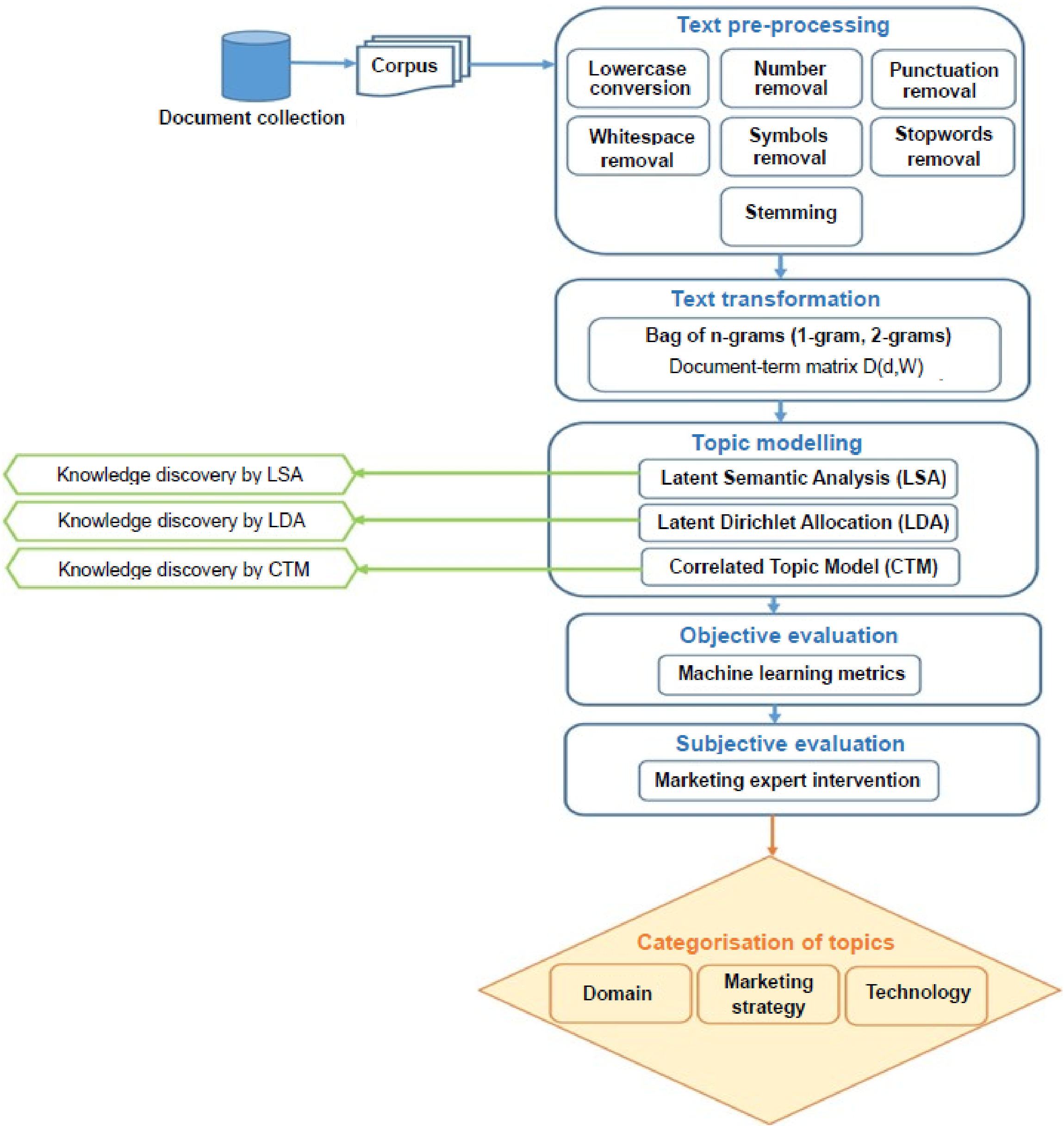

Figure 1. The topic modelling process used in this research

Topic modelling process and techniques

Natural Language Processing (NLP) is a computer-based analytical method that automatically understands and analyses human language (Manning & Schutze, 1999). This allows scholars to easily extract useful insights from textual datasets while avoiding complex computational work (Collobert *et al.*, 2011).

Topic modelling is an NLP task that has gained widespread interest among researchers in several fields (Liu *et al.*, 2016). Topic modelling is a powerful tool for extracting knowledge from a large volume of unstructured texts. When applied to a corpus of scientific articles, topic modelling reveals relationships between articles and generates hidden topics by clustering

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words or expressions with similar meanings from the corpus. Each topic comprises a collection of words from the vocabulary of the corpus and each document contains a mixture of topics.

The application of topic modelling techniques to a large corpus of documents requires a researcher to prepare the corpus for processing and to make decisions about the algorithm's parameters. The commonly used topic modelling techniques for analysing a collection of papers in the field of marketing are LSA, LDA and CTM (Chebil *et al.*, 2021).

(1) LSA is one of the fundamental non-probabilistic techniques of topic modelling. LSA represents the corpus as a document-term matrix, then uses the dimensional method reduction by singular value decomposition (SVD) and projects the matrix into a K-dimensional topic space. This projection makes it possible to retrieve the pertinent documents in the low-dimensional topic space in place of the original space (Tu *et al.*, 2017).

(2) LDA is a generative probabilistic technique that forms the basis of many other topic modelling techniques. LDA is the most used in the literature. The basic idea is that each document is shown as a random mixture over latent topics where each topic is characterised by a distribution over the words. The weights of topics vary from one document to another (Jelodar *et al.*, 2018). LDA uses the Dirichlet distribution to model the variability among the topic proportions (Blei & Lafferty, 2007).

(3) CTM is also a probabilistic technique that could be considered as a variant of LDA. CTM replaces the Dirichlet prior with a normal prior using a Gaussian covariance matrix to overcome LDA's limitation in describing topic correlations (He *et al.*, 2018). According to Kampas (2022), the key idea behind CTM is that a document dealing with medicine is more likely to be related to disease than astronomy.

In this research, LSA, LDA and CTM are applied to a corpus consisting of 60 articles within the field of clustering social media data and marketing. These articles were collected using the same criteria as those utilised by two previous researchers: Benslama and Jallouli (2020) that will be designed as Study 1; and Chebil *et al.* (2021) so far called Study 2. The selection of the same criteria for selecting papers allows comparison of this research's results that are obtained by applying topic modelling techniques on abstracts, titles and keywords, with previous results obtained using manual thematic analysis of full texts (Study 1) or applying topic modelling techniques on a smaller dataset (Study 2). The collection comprises scientific papers published between 2016 and 2021, obtained from Google Scholar and Science Direct databases. The search retained the following terms: 'marketing,' 'social media' and 'clustering'. The distribution of articles by year is presented in Table 1.

Table 1. Number of articles studied per year

Year	Number of articles
2016	3
2017	6
2018	3
2019	4
2020	4
2021	40

Topic modelling assumes that the number of topics *k* must be fixed before generating the model on any corpus. In the literature, there is no method that determines the real optimal number of topics. Existing methods generally give an approximately value. We therefore adopted the following objective evaluation metrics for deciding the optimal number of topics *k*: probabilistic coherence, perplexity, R-squared (Arun *et al.*, 2010; Cao *et al.*, 2009; Griffiths & Steyvers, 2004). Then, a marketing expert was consulted to judge the quality of the best topic modelling for LSA, LDA and CTM resulting from the quantitative evaluation. Additionally, the marketing expert has classified results by fields, marketing strategies and technologies.

For each technique, the top 10 words of each latent topic are analysed to determine relevant, irrelevant and duplicate topics. Furthermore, topic labels (tags) which are computed by an algorithm based on *P(bi-gram | topic) – P(bi-gram)* are revised. The bad labels are replaced with new expressive labels. Then the final labels are classified by fields, marketing strategies and technologies.

After classifying the final topic labels, the techniques are compared to each other to determine the best technique according to several parameters. The steps and processes of experts' contributions are explained below. We consider:

- Three levels of expertise: *E1* non-expert, *E2* medium expertise, and *E3* expert.
- Ten units of time (*T*) spent by experts when contributing to analysis and improving the results of topic modelling techniques: 1*T* to 10*T*.
- Three relevance levels of labels: *Q1* for lowest relevance, *Q2* for medium relevance and *Q3* for highest relevance of labels.

The quantification of expert contribution (effort) for each step in terms of *T*, *E* and *Q* are as follows:

1. Check the relevance of automatically generated labels (*E3*, 4*T* per topic).
2. Spot duplicated topics (based on auto-generated labels) (*E1*, 1*T* per topic).
3. Spot the non-relevant topics (*E3*, 4*T* per topic).
4. Improve labels based on generated top terms (*E3*, 2*T* per topic).

5. Classify labels into fields, marketing strategies and technologies ($E3$, $2T$ per topic).
6. Spot duplicated revised topics ($E2$, $2T$ per topic).

Main Results and Discussions

The optimal number of topics

To determine the optimal number of topics k and the best model, the three techniques LSA, LDA and CTM are evaluated with several metrics on a range of topics from 2 to 59.

First, the probabilistic coherence measure computes the coherence score of topics. The topic modelling technique which has the highest probabilistic coherence score is the best model. Results show that LSA and LDA are better than CTM.

Second, R-squared measures the goodness of fit of topic model according to value of k. When the R-squared value is approached to 1 the regression predictions perfectly fit the data. According to the results displayed in Table 2, based on these two metrics the model ranking is as follows: LSA is rated the best, followed by LDA and then CTM.

Third, the perplexity metric evaluates the performance of probability models and cannot be applied in an algebraic model. The lowest perplexity value indicates a better model. Thus, the CTM model is better than the LDA model (Table 2).

Table 2: Objective comparison of topic modelling techniques

Metrics	LSA	LDA	CTM
Probabilistic coherence	0.98333 ($8<k<59$)	0.98333 (k=32, 39, 43, 45, 47, 50, 54, 56, 57 and 59)	0.77666 (k=39 and 41)
R-squared	0.99653 (k=59)	0.76796 (k=56)	0.76796 (k=57)
Perplexity		124.1171 (k=56)	70.88122 (k=58)

Moreover, we use three different metrics (Arun *et al.*, 2010; Cao *et al.*, 2009; Griffiths & Steyvers, 2004) to evaluate the quality of the LDA model and determine the optimal number of topics. The optimal number of topics corresponds to the minimal values of Griffiths2004 and CaoJuan2009 metrics and the maximal value of the Arun2010 metric (Arun *et al.*, 2010; Cao *et al.*, 2009; Griffiths & Steyvers, 2004). Based on these three metrics, the optimal number of topics of LDA is in the range of 36 to 49.

We conclude that the evaluation metrics provide several choices for the optimal number. They give approximate values, and the expert/researcher decides which value to adopt. In this work, we choose the optimal number of topics as 39 for LSA, LDA and CTM based on the probabilistic coherence metric.

Contribution of experts and evaluation steps

This study deploys the judgement of marketing experts to evaluate and improve the quality of the output of LSA, LDA and CTM when the number of topics *k* is 39. Table A1 (in the Appendix) shows the evaluation steps as well as the details of the experts' operations in each step.

According to Table A1, LDA gives the best relevance (quality) of topic modelling *(Q3),* while LSA and CTM have medium quality *(Q2)*. Moreover, LDA provides a higher number of relevant topics *(27)* whereas CTM gives *(22)* and LSA gives *(21)*. In addition, LDA requires a higher level of expert tasks detailed in terms of time units *(276 T)*, while CTM has a lowest effort from the experts *(258 T)*. In addition, LDA requires a higher level of expertise and time per topic to categorise topics *(54 T)*. Consequently, the choice between these three techniques depends on:

- The final number of relevant topics: LDA *(27 topics)* then CTM *(22 topics)* then LSA *(21 topics)*.
- The quality/relevance of the topics: LDA *(Q3)* then CTM *(Q2)* and LSA *(Q2)*.
- Level of expertise and time per topic to categorise topics by fields, marketing strategies and/or technologies: LSA *(42 T)* then CTM *(44 T)* then LDA *(54 T)*.
- Total number of spent time units by experts to validate the relevant topics: LSA *(258 T)* then CTM *(261 T)* then LDA *(276 T)*.

These results could guide future marketing research to select the best topic modelling technique based on available time and expertise.

Categorisation of topics

Table A2, Table A3 and Table A4 (in the Appendix) demonstrate the final topic labels generated by LSA, LDA and CTM techniques and treated by the expert. The topics are labelled with stems due to the data pre-processing step. For instance, the label 'machin_learn represents 'machine learning'. These topics labels are assigned to one or more of the three categories: fields, marketing strategies and technologies. The terms on the same line in the tables constitute the topic label as revealed by the topic modelling technique. For example, the label 'media_market (cinema_market) & machin_learn' was assigned to two categories, Fields and Technologies.

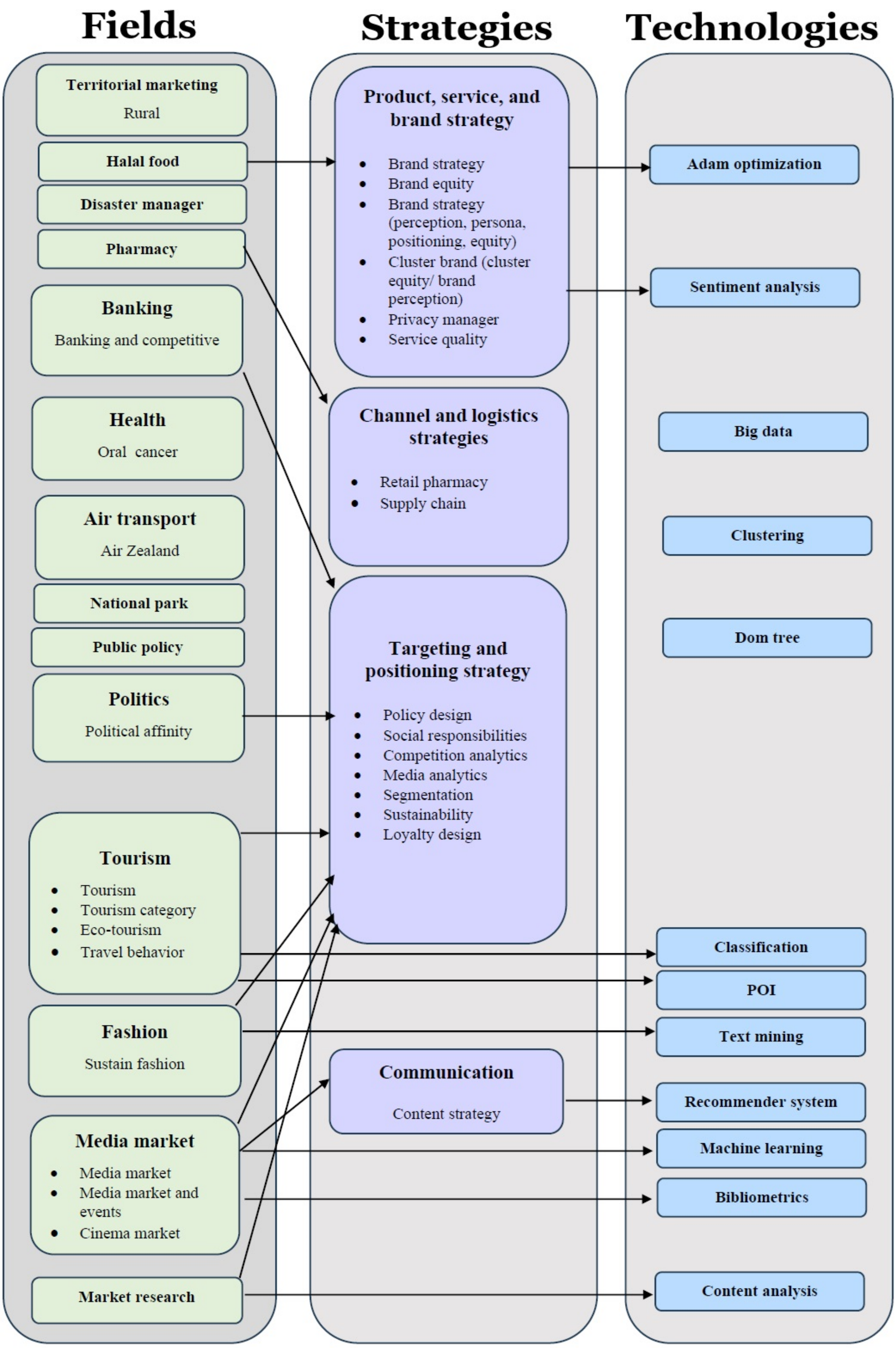

Figure 2. Overview of clustering techniques and technologies for marketing strategies (outputs of the topic modelling process)

Figure 2 presents a cartography of the main findings of this research. We integrated the results from three different topic modelling techniques that were applied to automatically analyse articles pertaining to the clustering of social media and marketing. Subsequently, a marketing expert has reviewed and categorised the topics based on fields, marketing strategies and technologies. We then grouped the fields into categories and organised the strategies generated by these techniques according to the five most commonly utilised marketing strategies as identified in existing literature.

Figure 2 illustrates that within the corpus of articles, the three categories (fields, marketing strategies and technologies) are occasionally found together. In some instances, a subset of the articles focuses exclusively on topics related to fields, marketing strategies or technologies. There are also cases where a combination of two topic categories is present within the same set of articles (a portion of the articles in the entire corpus).

The results of our study revealed that the most commonly employed strategies in the articles we analysed are targeting and positioning strategy; communications and influence strategy; channel and logistics strategies; and product, service and brand strategy. Pricing strategy was not prominently featured in this collection of documents. This could be due to our analysis with topic modelling techniques focusing solely on the "title', 'abstract' and 'keywords' sections of the articles. Alternatively, the absence of this strategy in the collection of articles may indicate that they are mentioned in only a few documents within the corpus. Another possibility is that this strategy is not commonly used in conjunction with the fields found in these articles.

Moreover, our study's findings indicate that the analysis of articles in the domain of social media data marketing encompasses various subfields within the marketing discipline. The identified subfields include: territorial marketing (rural), halal food, disaster manager, pharmacy, banking, health, air transport, national park, public policy, politics, tourism, fashion, media market and market research.

The results have revealed other clustering-related techniques and technologies, such as a recommender system, the Adam optimisation algorithm, which is a deep learning algorithm employed to enhance the accuracy of neural networks by adjusting the learnable parameters of the model (Kingma & Ba, 2014), the DOM (Document Object Model) tree, which is a programming API for HTML and XML documents, and the technology of points of interest (POI) data, which pertains to the digital representation of physical locations that people may find useful or interesting. Commercial establishments like restaurants, shops and hotels can be considered as POIs. Moreover, a POI can be a public place, such as a park, museum, school or a hospital. Recent research underscores the integration of clustering with various

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technologies, playing a crucial role in different applications. In recommender systems, clustering enhances personalised recommendations and aids in group-level popularity prediction (Bohra & Bhatnagar, 2021). The Adam optimisation algorithm extends its impact to clustering, ensuring faster convergence during training and boosting clustering model efficiency (Hu *et al.*, 2019). DOM trees contribute to clustering for web document segmentation, highlighting the importance of hierarchical organisation (Sarma & Mahanta, 2019). POI data benefit from clustering, evidenced in collaborative clustering and spatial analysis, showcasing clustering's ability to extract meaningful patterns Yang *et al.*, 2011; Athanasiou *et al.*, 2019). The synergistic combination of these technologies and clustering techniques results in heightened accuracy, efficiency and insights across diverse data-driven applications.

Comparison with previous studies

This section aims to conduct a comparative analysis between the results of the current study and two earlier publications that employed the same data collection method. The objective of this comparative analysis is to offer insights into the variations and developments in clustering data analytics and marketing across the specified periods. The studies concerned in this comparison are:

(1) The research of Benslama & Jallouli (2020) who have adopted the same method of collecting 20 scientific papers dealing with clustering data analytics and marketing published from 2016 to 2019. This research performed a manual content analysis of titles, abstracts and full texts, without performing topic modelling tools. The output consists of a list of 16 topics. This research is designated as Study 1.

(2) The research of Chebil *et al.* (2021) that retained the same corpus as Benslama & Jallouli (2020) and performed LSA, LDA and CTM techniques to extract respectively 10, 12 and 10 topics. This research is designated as Study 2.

(3) In the current research, 60 articles were retained, with 20 articles overlapping with the datasets used in Study 1 and Study 2. The remaining 40 articles are novel publications from 2021. LSA, LDA, and CTM techniques were employed, resulting in the extraction of 21, 27 and 22 topics, respectively. These topics were subsequently categorised into fields, marketing strategies, and/or technologies. The current research is designated as Study 3.

Table A5 (in the Appendix) shows that when the corpus is enlarged in Study 3, the number of relevant topics without redundancy increases to 30. Study 3 reveals new insight based on classifying the topics by fields, marketing strategies and technologies. Moreover, the comparison of the output of the three studies outlines that the topic 'Airlines' is revealed in Study 1 and in Study 2 but it does not appear in the results of Study 3. The reason is that the topic is linked to a single document in the corpus and when the corpus is enlarged, the number of occurrences of this word becomes low compared to the number of relevant words that appear in the whole corpus. Additionally, the topics 'Education', 'Sales and B2B' and 'Marketing analysis and wineries' are revealed in Study 1 and are not found in Study 2 and Study 3. The reason is that the words of these three topics appear with great frequency in the full text. Indeed, in Study 1 all the parts of the articles are analysed whereas in Study 2 and Study 3 only the 'title', 'abstract' and 'keywords' are analysed. This finding highlights the relevance to extend the study to the full text in future work in addition to titles, keywords and abstracts.

In addition, the evaluation performed by marketing experts indicates that LDA model is the best technique in terms of quality and number of relevant topics but it needs a greater contribution from experts. Comparing this result with Study 2, we conclude that LDA still ranks first. Table A6 (in the Appendix) presents a summary of the comparison classification of topic modelling techniques.

LDA renders better results in terms of quality and number of relevant topics and requires more operations handled by experts. The high cost of expert contribution needed by LDA could be explained by the higher number of related topics, which requires more expert effort to process results.

The added value of this work according to Chebil *et al.* (2021) is the classification of topics which is extremely insightful for marketing practitioners and researchers. Indeed, a topic can express one or more features of the following categories: fields, marketing strategies and technologies. The analysis of the actualised corpus indicated that the articles published in 2021 had taken a new direction in terms of fields, marketing strategies and technologies. For example, disaster management, health issues, public policies and sustainability orientation are revealed as new domains of research in the marketing literature dealing with clustering social media. This result could be explained by the pandemic context that affected the global socio-economic features in 2021 and influenced in a significant way the topics studied by marketing researchers. Indeed, discussions of virtual communities constitute a valuable mine of information that could determine relevant clusters of target segments and consequently shape marketing strategies (Ayachi & Jallouli, 2022). In addition, this comparative study revealed new techniques and technologies that are evoked in the papers published during 2021, such as sentiment analysis, classifications, recommender systems and machine learning techniques. This result draws marketing managers' attention to the growing role of big data analytics to analyse datasets related to customer comments and experiences shared on social media, e-commerce platforms and CRM systems, especially in the field of tourism, banking, supply chain and media content.

Conclusion

In recent times, there has been a notable surge in scientific articles related to social media data and marketing, reflecting the growing interest in this field. Researchers and decision-makers seek to automatically extract relevant information from this extensive body of literature to enhance marketing decisions. Topic modelling techniques have emerged as a valuable tool for automatically uncovering knowledge from large collections of articles. The aim of this study is to review the literature on clustering social media data in the context of marketing and to compare the three topic modelling techniques – LSA, LDA, and CTM – as techniques used for this purpose. We applied these three techniques to automatically analyse a corpus of 60 articles dealing with clustering in the marketing context. Our evaluation process incorporated both objective and subjective assessments, revealing that LDA proved to be the most effective technique. We recommend that both researchers and marketers leverage LDA for their endeavours.

Our analysis yielded a spectrum of topics, which were subsequently categorised manually into fields, marketing strategies and technologies. These results shed light on the prominent domains, the prevailing strategies, and the techniques and technologies that outperform conventional clustering methods within marketing research. Additionally, our examination unveiled substantial correlations between strategies and techniques within particular domains, underscoring their interrelated nature.

The results of this paper have contributed to establishing an overview of clustering techniques for marketing strategies. This overview integrates related fields (Figure 2), providing a new conceptual tool for future research in SMDA and marketing strategies. The results are also of great interest to practitioners who are eager to define the best techniques and technologies to use in order to extract knowledge from available social media data.

Future research could build on these results and implement classification techniques to automatically sort topics into fields, marketing strategies and technologies. By expanding the number of documents in the corpus, it is anticipated to extract a broader range of marketing knowledge. Exploring alternative techniques, such as Top2Vec and BERTopic for scientific paper corpus analysis through topic modelling and text mining, is encouraged. These approaches leverage unsupervised neural networks to create distributed representations of texts and words (Krishnan, 2023). Furthermore, marketing experts can employ additional subjective evaluation criteria, such as assessing the novelty of topics. Novelty measures the

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extent to which the topics offer fresh or unique insights not commonly known, highlighting the uniqueness of the information.

This research has benefited extensively from the collaboration between marketing experts and data scientists and encourages further joint projects for a deeper understanding of the performance of several topic modelling tools.

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Appendix

Table A1. Subjective comparison of topic modelling techniques

Criteria	Step	Level of expertise/ time per topics	Interventions	LSA K=39	LDA K=39	CTM K=39
Label task	1	*E3, T4*	Check the relevance of automatically generated labels	39 (*T4*)	39 (*T4*)	39 (*T4*)
	2	*E1, T1*	Spot duplicated topics (based on automatically generated labels)	18 (*T1*)	12 (*T1*)	17 (*T1*)
	3	*E3, T4*	Spot the non-relevant topics	0	0	0
	4	*E3, T2*	Improve labels based on generated top terms	21 (*T2*)	27 (*T2*)	22 (*T2*)
	5	*E3, T2*	Categorised labels into fields, marketing strategies and/or technologies	21 (*T2*)	27 (*T2*)	22 (*T2*)
	6	*E2, T2*	Spot duplicated revised topics	0	0	0
Total T	-	-	-	258 T	276 T	261 T
Relevance of output	-	*Q2, Q3*	-	*Q2*	*Q3*	*Q2*
Number of validated topics				21	27	22

Table A2. Topic labels generated by LSA after expert contribution

LSA		
Fields	**Strategies**	**Technologies**
media_market (cinema_market) &		machin_learn
tourism (travel_behaviour/ eco-tourism)		
disast_manag		
sustain_fashion		
oral_cancer		
nation_park		
halal_food		
banking and competitive intelligence		
pharmaci		
rural (territorial marketing)		
supply_chain		
	content strategy	
	brand_equiti &	adam_optim
	brand strategy	
	privaci_manag &	Sentiment_analysis
	privacy_manag	
		big_data
		recommend_system
		machin_learn
		DOM tree
		classification
Total: 11	**Total:** 5	**Total:** 8

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Table A3. Topic labels generated by LDA after expert contribution

LDA		
Fields	**Strategies**	**Technologies**
tourism_categori &		classification
tourism_categori		
travel_behaviour		
disast_manag		
sustain_fashion &		text_mining
oral_cancer		
nation_park		
halal_food		
polit_affin		
competit_analysis (banking)		
pharmaci &	polici_design	
rural (territorial marketing)		
media_market and events &		bibliometrics
public_policy		
market_research (segmentation) &		content_analysis
social_respons (responsibilities)		
	brand_strategy (perception, persona, positioning, equity)	
	servic_qualiti	
	privaci_manag	
		big_data
		adam_optim
		recommend_system
		machin_learn
		sentiment_analysis
		DOM tree
		POI
		clustering
Total: 16	**Total:** 4	**Total:** 12

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Table A4. Topic labels generated by CTM after expert contribution

CTM		
Fields	**Strategies**	**Technologies**
media_market &		recommend_system
media_market (media_analysis) &		machin_learn
tourism_categori &		POI
travel_behaviour (destin_loyalti)		
disast_manag		
sustain_fashion		
oral_cancer		
nation_park		
halal_food		
polit_affin		
banking		
retail_pharmaci		
public_policy &	polici_design	
market research		
air_Zealand		
supply_chain		
media_market &	content_strategy	
	cluster_brand (cluster equity/ brand perception)	
	privaci_manag	
		clustering
		adam_optim
		classification
Total: 17	**Total:** 4	**Total:** 6

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Table A5. Comparison of results with previous research

Study 1	Study 2			Study 3		
16 topics	LSA 10 topics	LDA 12 topics	CTM 10 topics	LSA 21 topics	LDA 27 topics	CTM 22 topics
Travel	travel_behaviour	travel_behaviour	big_data and travel	tourism (travel_behaviour/ eco-tourism)	tourism_categori travel_behaviour	tourism_categori & POI travel_behaviour (destin_loyalti)
Consumer perception and behaviour	brand_percept	brand_percept		brand_equiti & adam_optim brand strategy	brand_strategy (perception, persona, positioning, equity)	cluster_brand (cluster equity/ brand perception)
Airport marketing and airline industry	airlines	airlines	Brand_percept and airport_airlines			
Market segment-ation	market segmentation		market segmentation		market research (segmentation) & content analysis	market research
Brands and cosmetic products	brand_percept	brand_percept	cluster_brand	brand_equiti & adam_optim brand strategy	brand_strategy (perception, persona, positioning, equity)	cluster_brand (cluster equity/ brand perception)
Banking	competitive strat in banking	competitive strat in banking	competitive strat in banking	banking and competitive intelligence	competit_analysis (banking)	banking
Supply chain manag		supply_chain	supply_chain	supply_chain		supply chain
Education						
E-commerce and privacy behaviours	privacy manag	privacy manag	privacy manag	privaci_manag & sentiment analysis privaci_manag	privaci_manag	privaci_manag
Halal food	halal_food	halal_food	halal_food and travel	halal_food	halal_food	halal_food
Rare events	media-activ and event	media-activ and event			media_market and events & bibliometrics	
User generated Content and video marketing		content strategi		content strategy media market (cinema market) & machin_learn		media market & content strategy
Sales and B2B						

Study 1	Study 2			Study 3		
16 topics	LSA 10 topics	LDA 12 topics	CTM 10 topics	LSA 21 topics	LDA 27 topics	CTM 22 topics
Rural e-marketing		rural e-marketing	rural e-marketing	rural (territorial marketing)	rural (territorial marketing)	
Marketing analysis and wineries						
New media and political marketing	polit_affin	polit_affin	polit_affin		polit_affin	polit_affin
	big_data	big_data		big_data	big_data	
					adam_optim	adam_optim
				recommend_system	recommend_system	media_market & recommend_system
				machin_learn media_market (cinema_market) & machin_learn	machin_learn	media_market (media_analy) & machin_learn
				privaci_manag & sentiment_analysis	sentiment_analysis	
				DOM tree	DOM tree	
					POI	
				classification	tourism_categori & classification	classification
				disast_manag	disast_manag	disast_manag
				sustain_fashion	sustain_fashion & text mining	sustain_fashion
				oral_cancer	oral_cancer	oral_cancer
				nation_park	nation_park	nation_park
				pharmaci	pharmaci & polici_design	retail_pharmaci
					public policy	public policy & polici_design
					servic_qualiti	
					social_respons (responsibilities)	
					clustering	clustering
						air_Zealand

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Table A6. Synthetic comparative table of topic modelling techniques

Evaluation criteria	Study 2 (20 papers)						Study 3 (60 papers)					
	LSA		LDA		CTM		LSA		LDA		CTM	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Number of relevant topics	10	2	12	1	10	2	21	3	27	1	22	2
Contribution of experts to categorise labels	–	–	–	–	–	–	*42 T*	1	*54 T*	3	*44 T*	2
Contribution of experts with label automatically generated	*123 T*	2	*128 T*	3	*97 T*	1	*258 T*	1	*276 T*	3	*261 T*	2
Quality of topics	*Q2*	2	*Q3*	1	*Q2*	2	*Q2*	2	*Q3*	1	*Q2*	2

Marketing Strategy and Artificial Intelligence

State of the Art and Research Agenda

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Abstract: The marketing literature highlights the growing integration of artificial intelligence (AI) into marketing strategies. Several publications show that this field is attracting increasing interest from researchers. The purpose of this article is to provide an overview of academic publications related to AI and marketing strategies, while also examining the lack of bibliometric analysis in this area. In this study, 1100 articles, published in the Scopus and Web of Science databases, were selected and, according to a consistent search procedure, were examined. A performance analysis, based on bibliometric indicators, revealed the most impactful journals, the most indexed authors according to H-index and the most cited papers. The thematic factorial map highlighted the typology of AI tools used in the field of strategic marketing, in this case the marketing strategy. It also provides a discussion, potential research avenues and recommendations for future investigations.

Keywords: Marketing strategy/strategic marketing, artificial intelligence, bibliometric analysis

Introduction

In upcoming years, artificial intelligence (AI) is anticipated to substantially influence a range of marketing strategies, encompassing business models, sales methodologies, customer service alternatives, and consumer behaviour (Davenport *et al.*, 2019). The formulation of a marketing strategy necessitates deliberate decision-making by managers about the organisation's goals and the strategies to realize them. On the other hand, the execution of the marketing strategy entails converting these decisions into intricate and cohesive marketing

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approaches, bolstered by suitable actions and allocation of resources (Slater *et al.*, 2010). Research by Huang & Rust (2021) indicates that AI has the potential to suggest target market segments, grounded in historical purchase data and customer preferences. Additionally, AI can aid in product positioning by discerning resonance market segments, clusters of consumers with analogous needs and preferences for which a product holds the most relevance. In a similar vein, AI can facilitate customized customer interactions by presenting personalised offers specifically tailored to individual purchase patterns and predilections. Moreover, AI can foster emotional bonds with consumers by evaluating social engagements and crafting marketing messages aligned with their emotional states.

An examination of academic articles discussing AI and marketing strategy can yield a consolidated overview of AI's primary applications related to marketing strategies. This allows researchers to align their work with the current state of the art and shape their subsequent investigations. This analysis might further guide businesses in seamlessly and aptly integrating AI into their strategic marketing endeavours.

A literature review focusing on AI and its implications in marketing underscores the abundance of academic contributions in this arena. Verma *et al.* (2021) emphasize that, due to the vast scope and volume of AI research in marketing, a meta-synthesis of existing studies is essential in determining the forthcoming research trajectory.

the marketing discipline, the "marketing strategy" construct is viewed as the central foundation for strategic marketing (Varadarajan, 2009; Hunt, 2015; Morgan *et al.*, 2018). Morgan *et al.* (2018) further prompt scholars to engage with specific research questions, thereby providing new avenues for knowledge development. This includes new methods for data collection regarding significant strategic marketing phenomena, as well as new tools for image analysis and their application to various marketing aspects.

Furthermore, drawing upon the Scopus and Web of Science databases, acclaimed for their exhaustive and trustworthy metadata (Pranckutė, 2021; Zhu & Liu, 2020), a discernible gap is identified: there is a lack of bibliometric analysis related to the interplay between AI and marketing strategy. This realization accentuates the significance of the current discourse, which seeks to address the following research questions (RQ):

RQ1: What specific methodologies and quantitative measures have been predominantly used to assess the impact of AI technologies on the effectiveness of marketing strategies across different industries?

RQ2: What are the primary themes and key findings that have emerged from the literature on the application of AI in marketing strategies?

RQ3: What are the explicit gaps in the current literature on AI in marketing, and which emerging AI technologies or marketing challenges require further empirical and theoretical exploration?

This manuscript is organized to first present a review of existing literature on marketing strategies and AI. This is followed by a discussion of the methodological choices applied in the study. Subsequently, the document details the results from the performance analytics. The paper then explores the critical components of factorial thematic mapping, which connects marketing strategies to AI applications. Further, the text offers a conceptual analysis and a keyword co-occurrence network. Towards the conclusion, the paper identifies existing research gaps, discusses the significance of the findings, and outlines the potential directions for future studies.

Literature Review

This section presents the concept of marketing strategy as an essential area of study within strategic marketing and offers insight into the interplay between AI and marketing strategy.

Strategic marketing and marketing strategy

It is essential to differentiate between the terms 'strategic marketing' and 'marketing strategy': while strategic marketing represents a broad academic domain covering diverse research areas, marketing strategy is a specific subset within it. However, not every strategic marketing study delves deep into the nuances of marketing strategy. Citing the influential work of Varadarajan (2009), endorsed by Hunt (2015), strategic marketing primarily focuses on studying organizational, inter-organizational, and environmental dynamics. It examines organizations' market behaviours, their interactions with various external stakeholders, and the managerial roles that shape marketing strategies in organisations.

Given that, the definition of marketing strategy is built upon the concept of marketing, defined by the American Marketing Association in 2007: "Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large" (Rownd & Heath, 2008, p. 1; Varadarajan, 2009, p. 120). Broadening this perspective, "marketing strategy can be defined as an organization's integrated pattern of decisions that specify its crucial choices concerning products, markets, marketing activities and marketing resources in the creation, communication and/or delivery of products that offer value to customers in exchanges with the organization and thereby enables the organization to achieve specific objectives" Varadarajan (2009, p. 119).

A synthesis of earlier research (Hunt, 2015) suggests that the Resource-Advantage theory (R-A theory) provides a theoretical foundation for four major types of business strategies: industry-focused strategy, resource-based strategy, competency-based strategy, and knowledge-based strategy. Furthermore, it identifies four pivotal marketing strategies, namely Market Orientation, Relationship Marketing, Market Segmentation, and Brand Equity Strategy.

Drawing on the work of Varadarajan (2009), Morgan *et al.* (2018) specify that marketing strategy is a fundamental construct at the core of the strategic marketing field. It is also "central to the practice of marketing". This construct encompasses strategy decisions and actions. Indeed, five facets define contemporary marketing strategy: "(1) decisions and actions, (2) differential advantages over competitors, (3) sustainable advantages, (4) a goal to enhance firm performance, and (5) the customer perspective" (Palmatier & Crecelius, 2019, p. 7).

Sozuer *et al.* (2020, p. 165) clarify that the marketing strategy is a "marketing logic" and point out the "creation of customer value to achieve business objectives".

In this context, five marketing strategies are enumerated by Kotler *et al.* (2017) and Campbell *et al.* (2020): (1) Segmentation, Targeting and Positioning strategies (STP); (2) Product/Services/Brands Strategy; (3) Pricing Strategies; (4) Distribution Channels and Logistics Strategy; (5) Integrated Marketing Communications and Influence Strategy.

The following section describes how AI reshapes decisions of marketing strategies as the principal focus of the strategic marketing field. As specified by the frameworks of Huang & Rust (2021), strategic marketing integrated three stages: research marketing, marketing strategy and marketing actions. Marketing strategy's decisions are developed through data collection, market analysis and customer understanding (thus, marketing research stage).

AI in the context of marketing strategy

Various interpretations of AI have been introduced by Davenport *et al.* (2019). AI "refers to programs, algorithms, systems and machines that demonstrate intelligence" (Shankar 2018, p. vi). It is characterized by machines exhibiting elements akin to human intelligence (Huang & Rust, 2018) and signifies machines that replicate cognitive human actions (Syam & Sharma, 2018). Central to AI are technologies such as machine learning, natural language processing, expert systems based on defined rules, neural networks, deep learning, tangible robots, and the automation of robotic processes (Davenport *et al.*, 2019). By utilizing these tools, AI can decipher external information precisely, assimilate learnings from this data, and manifest adaptive dexterity (Kaplan & Haenlein, 2019). Kumar *et al.* (2021, p. 5) indicate that "AI

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operates in the domain of continuous learning and automation, acting as the intelligence that drives data-based analytics and enables automated decision-making. AI can be broadly understood as a technology that is capable of imitating humans and carrying out tasks in a way that is considered 'intelligent'".

In the context of the marketing field, Marketing AI is defined as "the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome" (Overgoor *et al.*, 2019, p. 2).

Various types of AI in the context of marketing strategy are identified. For instance, Huang and Rust (2018) advocate that AI can be employed for marketing research, marketing strategy (segmentation, targeting, and positioning — STP), and marketing actions. They set out three types of intelligences (as humans have, for multiple tasks). Mechanical AI designed for automating repetitive tasks, can be utilized for data collection, data sensing, tracking (research stage) and can be harnessed for segmentation (segment recognition). Mechanical AI can be utilized for standardisation (4Ps/4Cs — Product, Price, Place and Promotion; Consumer, Cost, Convenience and Communication). Thinking AI, designed for market analysis, can be used for predictive analytics (research stage) and to recommend the best target segments (targeting). Thinking AI is used in marketing action to personalize products (customer preferences), customize promotional content, etc. Feeling AI is designed for understanding customers by using emotional data about their sentiments, feelings and attitudes (research stage). Feeling AI can develop positioning to understand what resonates with target customers. During the marketing action stage, feeling AI can be used for relationalization and for how 4P actions can be able to meet a consumer's needs and wants and to deliver consumer benefits.

Methodology

The methodology for the bibliometric analysis of the connection between Artificial intelligence and marketing strategy involved conducting a bibliographic search in Scopus and Web of Science (WoS) databases, focusing on English peer-reviewed documents published in scientific journals from 1986 to 2022. These sources were selected as they provide the most comprehensive and reliable metadata (Pranckutė, 2021; Zhu & Liu, 2020). This analysis was divided into two parts: performance analysis, which examined contributions to AI's role in marketing strategies; and science mapping, which addressed the relationships between these research components. Data gathering procedures included excluding documents that do not contain titles, abstracts and keywords, with a total of 1100 final documents extracted. Data analysis techniques encompassed metrics at both author and document levels, factorial analysis for co-words, t-network analysis, with the use of the R software package Bibliometrix

R4.3.2 and its web-based application Biblioshiny (Aria & Cuccurullo, 2017; Cuccurullo *et al.*, 2016). The methodology by Zhou *et al.* (2019) for co-occurrence network construction and thematic keyword mapping was adopted. This involved categorizing clusters based on prominent nominal phrases extracted from article titles, abstracts, and indexing terms, with representative phrases utilized as cluster summaries. The CiteSpace 6.2 R4 software was employed for this procedure, and the analysis was conducted using the betweenness centrality metric. This approach allowed for a comprehensive understanding of the interconnections and thematic patterns within the AI and marketing strategy literature, enabling the uncovering of emerging trends and key contributors in the field.

Document search query

The search query used to select the most relevant document base is provided in Table 1.

Table 1. Search query

Database	Search Query
Scopus	((TITLE-ABS-KEY («marketing strateg*"))) AND (TITLE-ABS-KEY (({artificial intelligence} OR {AI} OR {deep learning} OR {machine learning} OR {internet of things} OR {big data} OR {neural network*} OR {Natural language processing} OR {chatbot*} OR {robot*})) AND PUBYEAR > 1985 AND PUBYEAR < 2023 AND (LIMIT-TO (LANGUAGE, "English"))
Web of Science	(TS=[chatbot*]) OR (TS=[robot*]) OR (TS=[AI]) OR (TS="artificial intelligence") OR (TS="internet of things") OR (TS="neural network*") OR (TS="NLP") OR (TS="big data") AND (TS="marketing strateg*")

On August 16, 2023, a comprehensive search was executed using the Scopus and WoS databases. This search employed a combination of specific terms linked through Boolean operators. The query was designed to filter for articles with the term “marketing strateg*” (where the asterisk * serves to capture variants such as “strategy”) in the title, abstract, or keyword segments. Additionally, articles were selected if they incorporated at least one of the subsequent terms within the same sections: “AI”, “artificial intelligence”, “machine learning”, “deep learning”, “robot*”, “neural network*”, “chatbot*”, or “natural language processing”.

Figure 1 (Appendix A) summarizes the filtering of documents upon which the final analysis was conducted.

Bibliometric analysis of documents

The bibliometric assessment of this dataset unfolds in two distinct phases. Initially, a descriptive exploration was conducted utilizing the Bibliometrix package in R 4.3.2 software. This package facilitates the measurement of annual publication growth, pinpointing the most cited references or authors, as well as recognizing local citations and the most referenced local authors. Moreover, it determines the authorship dominance in the most prolific sources and evaluates their H-index. For the co-occurrence network construction and thematic keyword mapping, the methodology by Chen (2017) was adopted. This approach inherently categorizes clusters based on prominent nominal phrases extracted from article titles, abstracts, and indexing terms, deploying representative phrases as cluster summaries. This procedure employs the CiteSpace 6.2 R4 software and utilizes the betweenness centrality metric, which determines to what extent a specific node lies on the path connecting two other nodes within the network (Aria & Cuccurullo, 2017). Chen (2017) notes that high centrality values potentially identify innovative scientific publications.

Performance Analysis

In this section, the paper presents a description of the database utilized for the study and examines several performance indicators, including journals with high impact factors, the top ten most influential authors in the field, the five most cited papers, and the five references that have received the most citations.

Database description

In this section, an invaluable resource for conducting thorough bibliometric analysis is presented, offering indispensable insights into publication trends, authorship patterns, citation impact, and collaboration dynamics within a specific field of study. The selected database for this analysis is detailed in Table 2.

Table 2. Database overview

Description	**Results**
Main Information About Data	
Time Span	**1986-2022**
Sources (Journals, Books, etc.)	699
Documents	1100
Annual Growth Rate %	17.1
Document Average Age	4.36
Average citations per doc	9.531
References	20966
Document Contents	
Keywords Plus (ID)	3641
Author's Keywords (DE)	2807
Authors	
Authors	2598
Authors of single-authored docs	186
Author Collaborations	
Single-authored docs	225
Co-Authors per Doc	2.99
International co-authorships %	10.91

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Documents in the database span from 1986 to 2022. The 1100 documents were published across 699 different sources. The average annual growth rate of these documents is 17.1%. The average age of a document is 4 years and 4 months. On average, each document has been cited 10 times. A total of 2589 distinct authors have contributed to these documents, with 186 being published by single authors. On average, each document has been co-authored by 3 individuals. Notably, 10.91% of the co-authors are from foreign countries.

High-impact journals

This section offers a presentation of impactful journals based on their H-indexm, which is crucial for bibliographic analysis as it offers insights into the influence of academic publications, incorporating metrics such as total citations, number of published articles, and inaugural year, thereby providing a comprehensive understanding of the landscape of AI and marketing strategy research.

Table 3. Top high-impact journals

Journal	h_index	g_index	m_index	TC	NP	PY_start
Expert Systems with Applications	11	12	0.55	546	12	2004
Industrial Marketing Management	7	8	1	200	8	2017
Sustainability	7	11	1.4	142	14	2019
IEEE Access	6	10	0.75	110	14	2016
Journal of Retailing and Consumer Services	6	6	1.2	345	6	2019
Lecture Notes in Computer Science (including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	6	9	0.273	104	22	2002
ACM International Conference Proceeding Series	5	7	0.556	57	32	2015
International Journal of Production Research	5	6	0.714	217	6	2017
Journal of Business Research	5	6	0.714	203	6	2017
Journal of the Academy of Marketing Science	5	5	1	919	5	2019

*g-index: “is calculated based on the distribution of citations received by a given researcher’s publications” (Egghe, 2006).
**m-index: “is calculated by dividing h-index value by number of years since the author is active” (Srivastava *et al.*, 2021).

Table 3 provides a distribution of the most impactful journals based on their H-index. A minimum threshold of H-index equal to 5 was considered to qualify a journal as impactful. This table gives insights into various academic journals and conference proceedings, incorporating their H-index, total citations (TC), the number of published articles (NP), and their inaugural year (PY_start). The H-index, as defined by Hirsch (2005), measures a journal’s influence, and is determined by the number of articles and citations they receive. These journals have exhibited varied impacts in the fields of AI and marketing strategies, as

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shown through their metrics. For instance, *Expert Systems with Applications* has an established influence with an H-index of 11 and a g-index of 12. *Sustainability* is noteworthy, with an H-index of 7 and a g-index of 11. Journals like *Journal of Retailing and Consumer Services* and *Journal of Business Research* have high m values of 1.2 and 0.714, respectively, with an emphasis on top-tier articles. The *Journal of the Academy of Marketing Science* showcases an H-index and an m value of 5, indicative of its influential and consistent presence, with a total of 919 citations. In summary, these journals display varying impacts, ranging from established stability to noticeable growth in the realms of AI and marketing strategies.

By synthesizing the insights from these journals (Table 4), it is clear that AI is being used to automate and enhance strategic decision-making processes across different domains of business. AI helps in analysing large sets of data to uncover patterns and insights that inform strategies, aids in understanding and predicting consumer behaviour, and enables the creation of more personalized customer experiences. These journals collectively convey that the integration of AI within strategic management leads to more informed, efficient, and competitive business practices.

Table 4. Focus and contribution of impactful journals

Journal	Focus	Contributions
Expert Systems with Applications	Application of AI and ML in strategic management and marketing	Showcases how neural networks are used to understand consumer behaviour, business intelligence for service management, and AI models for customer recommendation systems. It stresses the use of data mining and decision support systems to improve digital marketing strategies
Industrial Marketing Management	Business-to-business marketing and the application of AI in industrial marketing and management	Discusses topics such as pricing strategies, customer relationship management, and innovation, with a special attention to how AI can enhance these areas in an industrial context.
Sustainability	Utilization of AI and machine learning for strategic insights in customer data to promote sustainability	Uses sentiment analysis, text mining, predictive modelling, and clustering for strategic decision-making, aiding organizations to improve service and maintain a competitive edge while focusing on sustainability
IEEE Access	Application of AI techniques to extract insights from big data	Targets understanding consumer behaviour, preferences, and needs by analyzing data from social media, reviews, and customer transactions
Journal of Retailing and Consumer Services	Application of IoT in retail grocery shopping and its impact on consumer behaviour	Analyzes consumer responses to IoT services, assisting retail managers in creating effective marketing strategies that prioritize consumer convenience
Lecture Notes in Computer Science	Integration of AI with strategic management across various industries	Showcases how AI, through personalized marketing, customer segmentation, and sentiment analysis, enhances decision-making and optimizes business resource allocation

Journal	Focus	Contributions
International Journal of Production Research	AI's role in strategic management, particularly in e-commerce	Studies the impact of online reviews and promotional marketing on product demand using neural networks and applies AI techniques like fuzzy association rule mining for pricing strategies
Journal of Business Research	AI applications in strategic management	Investigates how AI technologies such as machine learning, image classification, and text mining enhance decision-making and marketing strategies
Journal of the Academy of Marketing Science	Role of AI in strategic marketing practices	Proposes frameworks and models that utilize AI to automate tasks, process data for decision-making, and analyze customer interactions to optimize marketing research and strategy

Top influential authors

This analysis serves as a valuable resource for bibliometric analysis, offering insights into the scholarly impact and productivity of individual researchers within a specific field. It aids in evaluating their contributions and influence on the academic community, facilitating comparisons and assessments of their research output. Table 5 ranks the most influential authors in the literature concerning marketing strategy and AI. This study selected those who have published five or more papers.

Table 5. Top 10 influential authors

Author	h_index	g_index	m_index	TC	NP	PY_start
Li, Y.	6	7	1	52	8	2018
Chen, L.	4	9	0.571	222	9	2017
Chung, Y.	4	4	0.25	57	4	2008
Kim, J.	4	6	0.235	61	6	2007
Lee, S.	4	5	0.222	114	5	2006
Li, S.	4	9	0.167	181	9	2000
Liu, Y.	4	9	0.5	88	14	2016
Sakas, D.	4	6	0.444	42	8	2015
Wang, M.	4	5	0.4	155	5	2014
Wang, S.	4	8	0.571	124	8	2017

Top most cited papers

For a more thorough analysis of literature performance, it is essential to provide an extensive examination of recent research articles exploring the intersection of marketing and artificial intelligence. This examination illuminates various subjects, such as the profound influence of AI on marketing strategies and practices. Table 6 outlines the top most-cited papers with at least four citations.

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Table 6. Top 10 most cited papers

Document	Title	Year	Local Citations	Global Citations
Davenport *et al.* (2019)	How artificial intelligence will change the future of marketing	2019	12	429
Timoshenko & Hauser (2018)	Identifying Customer Needs from User-Generated Content	2018	5	164
Tong *et al.* (2019)	Personalized mobile marketing strategies	2019	5	92
Saura *et al.* (2021)	Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research	2021	5	61
Li (2000)	The development of a hybrid intelligent system for developing marketing strategy	2000	4	73
Liu *et al.* (2016)	A Structured Analysis of Unstructured Big Data by Leveraging Cloud Computing	2016	4	89
Chong *et al.* (2017)	Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews	2017	4	107
Ahani *et al.* (2019)	Market segmentation and travel choice prediction in Spa hotels through TripAdvisor's online reviews	2019	4	116
Giglio *et al.* (2019)	Using social media to identify tourism attractiveness in six Italian cities	2019	4	86
Sakas & Giannakopoulos (2021)	Big Data Contribution in Desktop and Mobile Devices Comparison, Regarding Airlines' Digital Brand Name Effect	2021	4	9

Davenport *et al.* (2019) delve into how AI will reshape marketing's future. Timoshenko & Hauser (2019) introduce a machine learning-based approach to streamline qualitative analysis by efficiently selecting relevant content from extensive user-generated content (UGC) sets, thereby refining the identification of customer needs compared to traditional methodologies. Tong *et al.* (2019) probe the increasing utilization of mobile usage data to craft more pertinent marketing strategies and targeted campaigns, leveraging clients' hyper-contextual information. They propose a framework for personalized mobile marketing strategies, integrating the traditional marketing mix model, emphasizing personalization across product, place, price, promotion, and mobile prediction domains. Saura *et al.* (2021) address the research gap on AI's application in business-to-business (B2B) digital marketing, presenting a literature review and employing multiple correspondence analysis to categorize Customer Relationship Management (CRM) types and their AI integrations. The outcomes offer a deep understanding of B2B digital marketing strategies grounded in CRM and AI. Li (2000) elucidates the development of a hybrid intelligent system to craft marketing strategies, amalgamating expert systems, fuzzy logic, and artificial neural networks. This system also integrates Porter's Five Forces and Directional Policy Matrices for strategic analysis. The benefits and functionalities of this hybrid system are expounded in depth, illustrating its support for strategic analysis and marketing decision-making.

Liu *et al.* (2016) demonstrate the importance of accurate sales forecasting for marketing strategies, particularly in the era of online social platforms. By leveraging cloud computing, machine learning, and text mining techniques on vast amounts of Twitter data, the study reveals that the information content and timeliness of Tweets significantly enhance forecasting accuracy compared to basic measures, like volume or sentiment. Furthermore, it highlights that Twitter data surpass other online sources, such as Google Trends or Wikipedia views, in predicting TV show demand due to its real-time nature and relevance to user behaviour. Chong *et al.* (2017) investigate the influence of online promotional marketing and online reviews on consumer product demands using electronic data from Amazon.com, revealing that variables from online reviews are generally better predictors compared to online marketing promotional variables, providing valuable insights for practitioners and offering a Big Data architecture incorporating Neural Network analysis for future research. Ahani *et al.* (2019) propose a hybrid machine learning approach for segmenting spa hotels and predicting travel choices using online review data from TripAdvisor, demonstrating its effectiveness in informing marketing strategies and optimizing expenditures in the hospitality industry. Giglio *et al.* (2019) utilize social media data, specifically geo-tagged photos from Flickr, to analyze user behaviour and determine the attractiveness of tourism sites in six cultural hubs in Italy. Through data analysis using Mathematica and machine learning models, the study identifies annual trends in photographic activity and demonstrates the effectiveness of the proposed methodology in providing insights into user behaviour and destination popularity. Additionally, the research underscores the potential of social data analysis in creating predictive models for formulating tourism scenarios and discusses implications for general tourism marketing strategies. Sakas & Giannakopoulos (2021) investigate factors influencing airlines' organic traffic and user engagement, employing a three-stage data-driven analysis involving website and crowdsourcing data, Fuzzy Cognitive Mapping, and predictive modelling to offer actionable digital marketing strategies for optimizing user engagement.

Top most cited references

In this section, we will shine a spotlight on the references that embody the key concepts, theories, and practical tools used in the AI and marketing strategy literature. These references are like the guiding stars, leading researchers to valuable insights and methodologies. They are the trusted companions on the journey of exploring how artificial intelligence intersects with marketing strategies. Think of them as the pillars supporting the bridge between theory and practice in this dynamic field. Their influence shapes the landscape of research, providing the foundation for understanding and applying AI in marketing contexts. Table 7 indicates the most frequently cited references, with at least 10 citations, associated with AI and marketing strategies.

Table 7. Top 10 most cited references

Cited Reference	Citations
Chen *et al.* (2012), Business Intelligence and Analytics: From Big Data to Big Impact	16
Erevelles *et al.* (2016), Big Data consumer analytics and the transformation of marketing	16
Fornell & Larcker (1981), Evaluating Structural Equation Models with Unobservable Variables and Measurement Error	15
Gandomi & Haider (2015), Beyond the hype: Big data concepts, methods, and analytics	13
Huang & Rust (2018), Artificial Intelligence in Service	13
Davenport *et al.* (2019), How artificial intelligence will change the future of marketing	12
Davis (1989), Perceived usefulness, perceived ease of use, and user acceptance of information technology	12
Venkatesh *et al.* (2003), User Acceptance of Information Technology: Toward a Unified View	12
Dwivedi *et al.* (2021), Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	10
Lemon & Verhoef (2016), Understanding Customer Experience Throughout the Customer Journey	10

Chen *et al.* (2012) offer a comprehensive overview of Business Intelligence & Analytics (BI&A) evolution, applications, and emerging research domains, outlining and elaborating on BI&A 1.0, 2.0, and 3.0. The authors also scrutinize current BI&A research, pinpoint challenges and prospects in BI&A research and education, and provide a bibliometric study on publications, scholars, and pivotal subjects in BI&A spanning over a decade of academic and industry releases. Erevelles *et al.* (2016) explore consumer analytics' role in the Big Data revolution. They present a resource-based theoretical framework to understand how physical, human, and organizational resources shape the collection, information extraction, and utilization of vast consumer data to enhance firms' dynamic and adaptive capabilities. The framework also addresses specific resource requirements to harness Big Data's benefits in marketing.

Fornell & Larcker (1981) scrutinize the limitations of widely used statistical tests in analysing structural equation models with unobserved variables and measurement errors, highlighting issues related to the chi-squared test and its sensitivity to discrepancies between theoretical models and observed data. They introduce a test system based on shared variance measurements within structural and measurement models, aiming to assess model fit and

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explanatory power. Gandomi & Haider (2015) proffer an expansive definition of Big Data, encompassing its unique characteristics and focusing on analytic methods tied to unstructured data. They underline the imperative of crafting tools for structured data while sidestepping potential pitfalls tied to massive data size and intricacy. Huang & Rust (2018) inspect AI's transformative influence on service sectors, suggesting an AI-based job replacement theory rooted in four types of intelligence required for service tasks. They delineate the evolutionary order of AI development and its ramifications on professional tasks, stressing the shift from analytical to intuitive and empathetic skills as AI increasingly undertakes tasks, culminating in potential threats to human employment.

Collectively, these papers probe how AI can be harnessed to refine the understanding of consumer needs, develop user data-driven personalised marketing strategies, and re-evaluate the skills needed in the service sector as AI gradually takes over specific tasks.

Topic trends

Topic trends analysis in bibliometrics is essential for understanding how themes in AI and marketing strategy literature evolve over time, helping researchers identify emerging trends and inform future research directions. By tracking the prevalence, influence, and impact of specific topics, this analysis provides valuable insights for both academia and industry, guiding decision-making processes and resource allocation in research and business strategies. Appendix B presents the temporal evolution of the literature keywords. It indicates that the evolution of AI and marketing strategy literature reveals a fascinating journey from traditional approaches to cutting-edge, data-driven methodologies. Initially, concepts like "Fuzzy Logic" and "Neural Networks" paved the way for exploring computational methods in marketing strategy. As technology advanced, the rise of "Data Mining" and "Decision Support Systems" signalled a shift towards more evidence-based decision-making processes. Subsequently, the emergence of social media and digital marketing reshaped the landscape, emphasizing the importance of concepts like "Social Network" and "Digital Marketing" in consumer engagement. More recently, the rapid growth of AI and machine learning, coupled with responses to contemporary events like COVID-19 and the Internet of Things, underscores the need for marketers to adapt, innovate, and harness emerging technologies to stay ahead in an ever-evolving market.

Factorial Analysis of the Thematic Map

Factorial analysis is highly pertinent to bibliometric studies as it enables the identification of semantic relationships and thematic clusters within extensive datasets, offering valuable insights into the structure and organization of literature within a specific field, such as AI and strategic management. By examining the height between words, researchers can uncover patterns, trends, and associations among different concepts or topics, thereby enhancing their understanding of the scholarly landscape and contributing to the advancement of knowledge in the field (Aria & Cuccurullo, 2017). Figure 2 (Appendix A) illustrates a Thematic Factorial Map that allows a visual understanding of the relationships between different thematic categories and the keywords that define them. The position of each keyword on the dimension 1 (dim 1) and dimension 2 (dim2) axes of the chart indicates its relationship with other keywords within the same category (Wang & Si, 2023). Dimension 1 captures 43.63% of the variation in keywords. Dimension 2 on the y-axis explains an additional 13.22%. The two axes dim 1 and dim 2, encompass around 57% of what distinguishes strategy marketing research involving AI. Keywords that are closer to each other on the chart belong to the same category and are more strongly related. The extent to which each keyword is distanced from the origin represents its variance from a typical response pattern. Specifically, keywords that align with prevalent category traits are positioned closer to the origin, while those with distinct attributes are situated further away.

Initially, on the left side of the upper median axis, it is noted that CRM strategies are associated with data mining and machine learning, particularly in the context of marketing strategy and artificial intelligence. The topics in Dimension 1 encompass techniques like deep learning, big data, and social media analysis for personalized marketing campaigns and sentiment analysis. Dimension 2 focuses on customer relationship management, data mining, and machine learning applications to enhance customer interactions, segment customers effectively, and optimize marketing strategies based on data-driven insights.

Keyword Co-occurrence Network and Conceptual Analysis

The representation and examination of the keyword co-occurrence network are executed using the CiteSpace 6.2.R4 software. By selecting the “pathfinder” mode in the partitioning method and employing the Log-Likelihood Ratio (LLR) algorithm, nominal terms were extracted from the mentioned keywords, which serve as the designated labels for each cluster. Notably, the clusters of related keywords are labelled with terms that log-likelihood ratio (LLR) analysis revealed to be disproportionately present in the citations of those same concepts compared to other keywords. Each label captures the fundamental concept of each cluster through specialized language (Zhou *et al.*, 2019). Figure 3 (Appendix A) showcases the five most pivotal clusters based on the volume of documents that contributed to their inception.

The largest cluster (#0) has 95 members. It is labelled as *mining brand perception* by LLR. The major citing article of the cluster is Lamrhari *et al.* (2022), entitled “A social CRM analytic framework for improving customer retention, acquisition, and conversion". The most cited members in this cluster are *social media model* and *big data analytics*.

The second largest cluster (#1) has 77 members. It is labelled as *user-generated content* by LLR. The major citing article of the cluster is Boldt *et al.* (2016) entitled "Forecasting Nike's sales using Facebook data". The most cited members in this cluster are *machine learning*, *neural networks* and *forecasting*.

The third largest cluster (#2) has 74 members. It is labelled as *customer segmentation* by LLR. The major citing article of the cluster is Bae *et al.* (2007) entitled "Integration of heterogeneous models with knowledge consolidation". The most cited members in this cluster are *marketing strategy*, and *commerce and sales*.

The 4th largest cluster (#3) has 66 members. It is labelled as *big data technology* by LLR. The major citing article of the cluster is Zhang & Ma (2022), entitled "Online shopping brand sales based on IoT big data processing". The most cited members in this cluster are *big data, customer satisfaction and information systems*.

Cluster (#0): Mining brand perception

The conceptual map of clusters is determined through the application of centrality, a concept introduced by Freeman (1977), which measures a node's proximity to other nodes in a network by quantifying its incoming and outgoing connections. In this context, keywords at the bottom of the hierarchy exhibit high degree values, signifying strong connections, while those at the top have lower degree values, indicating weaker connections (De Bruyn *et al.*, 2023). The connections between these keywords are established based on the structure of the keywords' co-occurrence network. The conceptual map of the most important Cluster (#0) is presented in Figure 4 (Appendix A).

This cluster highlights the increasing role of AI and data-driven insights in shaping marketing strategies. Researchers are utilizing predictive analytics to forecast sales, predict customer behaviour, and identify significant marketing events through data from social media platforms such as Facebook, Twitter, and TripAdvisor. Customer segmentation remains a central focus in formulating effective marketing strategies, utilizing techniques like sentiment analysis and text mining. These findings resonate with a broader literature that emphasizes the significance of predictive analytics, social media data, customer segmentation, and text analysis in modern marketing. As AI and technology continue to advance, integrating data-driven insights into marketing strategies becomes increasingly crucial for businesses in the digital age. Table C1 (Appendix C) presents marketing strategy elements and the AI tools used to consistently analyze this strategy.

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Cluster (#1): "User generated content"

This cluster indicates a notable intersection between AI and marketing strategy methodologies. Keywords such as "sentiment analysis", "machine learning", "social networking", and "natural language processing" emphasize the pivotal role of sentiment analysis and AI in discerning customer requirements and refining strategic approaches. As shown in Figure 5 (Appendix A), the employment of machine learning methodologies and neural networks in analysing social and textual data, coupled with the assimilation of natural language processing, is emerging as fundamental to marketing enhancement. These components illustrate the transformative impact of AI on businesses' methodologies for customizing customer engagements, segmenting markets, and devising focused campaigns. Thus, this cluster showcases the innovative ways AI is reshaping marketing strategies by leveraging insights from social platforms and augmenting the comprehension of customer feedback.

Within the cluster analysis from documents that cite a minimum of ten keywords, several studies have been highlighted:

Boldt *et al.* (2016) and a subsequent publication by Boldt (2016) explore Nike's sales forecasting leveraging Facebook data. This underscores the potential of AI in sifting through social media data to predict business outcomes. Egebjerg *et al.* (2017) harness social data analytics to anticipate football viewership and television ratings, spotlighting AI's efficacy in inferring trends and outcomes from social metrics. Djebbi & Ouersighni (2022) present a dataset from Tunisia aimed at extracting topics and sentiments from social media, exemplifying the localized applications of AI in social media analytics.

Su *et al.* (2022) introduce a deep learning paradigm tailored to refine marketing strategies and elucidate customer nuances, reinforcing the transformative role of AI in optimizing marketing determinations. Argyris *et al.* (2020) investigate the ramifications of influencer marketing on Instagram, employing deep learning for the autonomic classification of images — a testament to AI's burgeoning role in visual marketing analytics.

Vaishanvi *et al.* (2022) advocate for an AI-driven sentiment-based product recommendation system, emphasizing the personalization capabilities of AI in aligning product suggestions with consumer emotions. Highlighting the promotional domain, Soguero-Ruiz *et al.* (2012) illustrate the merits of machine learning models in augmenting promotional campaign effectiveness.

In a study of Twitter's marketing dynamics, Serrano & Iglesias (2016) endorse viral marketing strategies, substantiated through agent-centric social simulations — a reflection of AI's instrumental role in gauging marketing strategy success. Sundsøy *et al.* (2014) draw a comparative analysis between machine learning outputs and conventional marketing expertise, suggesting AI's potential edge over intuition-led marketing methods.

Transitioning to the academic sphere, Min *et al.* (2021) venture into innovative methodologies in teaching market research and forecasting, spotlighting big data and AI's influential role in reshaping marketing pedagogy. Lastly, Al-Ghalibi *et al.* (2019) embark on an examination of sentiment dynamics on Twitter via natural language processing (NLP), showcasing AIs prowess in sentiment dissection and opinion mapping within social platforms.

Cluster (#2): Customer segmentation

As shown in Figure 6 (Appendix A), this cluster focuses on the intersection of AI and consumer segmentation within marketing strategies. It highlights the significance of leveraging AI techniques to gain insights into customer behaviour and optimize marketing initiatives. From predicting consumer shopping patterns using recurrent neural networks to utilizing AI-based customer relationship management (AI-CRM) for organizational performance, the cluster demonstrates how advanced AI tools are transforming traditional marketing approaches.

By adopting data-driven and machine learning-based customer segmentation, organizations can enhance their understanding of consumer preferences, resulting in more effective and profitable marketing strategies. Table C2 (Appendix C) presents AI and strategy marketing by cluster (#2) most cited documents.

Discussion

The bibliometric analysis applied in the domain of AI and marketing strategy demonstrates the growing importance of AI tools and techniques in shaping effective marketing strategies across various industries. These studies underscore how data mining, machine learning, sentiment analysis, and predictive modelling play pivotal roles in enhancing customer segmentation, predicting customer behaviour, and tailoring marketing approaches to specific contexts. AI is not only proving effective for customer relationship management and market segmentation but also for understanding consumer sentiment, informing brand communication, and predicting sales and engagement behaviour, reflecting its substantial impact on modern marketing practices.

This analysis showcases the versatility of AI in enhancing various aspects of marketing. It encompasses applications of AI in sales forecasting, audience prediction for football events, social-media data analysis for sentiment extraction, customer feature analysis, influencer marketing assessment, product recommendations based on sentiment analysis, promotional campaign optimization, viral marketing strategy validation, and even education in marketing

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research and market forecasting. This analysis collectively demonstrates the impact of AI on improving marketing practices, from understanding consumer sentiment to optimizing promotional campaigns and influencing marketing education.

The analysis findings highlight the transformative impact of AI on modern marketing strategy and customer segmentation across various industries. AI's role in enhancing marketing efforts is evident, particularly through its application in customer segmentation, allowing for precise targeting and increased customer satisfaction. In the B2B context, AI-based Customer Relationship Management (AI-CRM) offers valuable insights into improving organizational performance and competitiveness. AI's predictive capabilities extend to consumer behaviour, with Recurrent Neural Networks (RNNs) enabling the efficient prediction of customer behaviour. This empowers companies to implement more personalized marketing strategies. In healthcare, AI-driven data analytics are optimizing event selection and target market analysis for marketing managers, leading to improved marketing initiatives. The impact of weather data on consumer behaviour showcases AI's contribution to marketing decision support systems. AI can harness weather data to predict consumer preferences, resulting in more effective and cost-efficient marketing strategies. These findings collectively demonstrate the growing importance of AI-driven insights in tailoring marketing strategies to customer behaviour, ultimately fostering smarter and data-driven marketing campaigns that offer businesses a competitive advantage.

Conclusions, Limitations and Recommendations

This paper analyses literature on the convergence of marketing strategies and AI using a targeted search query in Scopus and WoS databases and subsequent bibliometric and performance analysis. The findings highlight a significant growth in AI-related marketing research, with pivotal works focusing on AI's role in consumer analytics, data-driven marketing, and the evolving service industry. These insights contribute to understanding how AI is reshaping marketing practices and strategy development.

Furthermore, the study examines the integration of AI in marketing strategies using Thematic Factorial Maps and Keyword Co-occurrence Networks analyzed via CiteSpace. It identifies key clusters: (1) AI-driven brand perception analysis, (2) AI applications in user-generated content for marketing strategy enhancement, and (3) Advanced AI techniques for customer segmentation. The research highlights AI's significant role in refining marketing strategies through predictive analytics and consumer behaviour insights.

This study allows novice researchers in the field of AI and marketing strategy to examine and synthesize the literature by referring to bibliometric indicators, such as the most impactful journals by H-index, the most indexed authors, the most cited articles, etc. According to the

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thematic factorial map, four themes (clusters) characterize research in this field: "Mining Brand Perception"; "User Generated Content"; "Customer Segmentation" and "Big Data Technology". The first theme represents the most important stream of research in this field.

All themes are anchored in one or other of the four marketing strategies: Market orientation; relationship marketing; market segmentation; and brand-equity strategy. AI is revolutionizing the field of marketing strategy by providing innovative solutions and insights. AI-driven tools and techniques are reshaping the way companies approach marketing, enabling data-driven decision-making and improved customer engagement. One common theme is the use of AI for analysing big data from sources such as social media, online reviews, and the Internet of Things (IoT). Machine learning and neural networks are employed for predictive analytics, aiding in sales forecasting, customer engagement, and sentiment analysis.

AI's role in social media marketing is prominent, particularly in understanding customer engagement behaviour, sentiment analysis, and brand perceptions. This enables companies to respond to customer feedback in real time and refine marketing strategies. AI also plays a crucial role in customer segmentation and personalized marketing, allowing companies to tailor strategies to specific customer segments, maximizing return on investment. The analysis of customer experiences through online reviews with AI and natural language processing offers valuable insights for marketing strategy and service quality improvements.

Lastly, the literature demonstrates the potential of AI in enhancing marketing strategies through IoT and big data analytics, as evidenced by the example of forecasting sales based on Facebook data. This highlights AI's capacity to predict sales and inform marketing strategies. AI's growing integration into marketing is expected to continue, providing data-driven, competitive strategies in an ever-evolving market landscape.

Research gaps are identified through the methodology of De Bruyn *et al.* (2023), which involves detecting the least developed clusters in the keyword co-occurrence network and analyzing unexplored themes in the literature emerging from these clusters. Among the primary research gaps identified in this thematic area, we note web shares, Predicting Variety-Seeking Customers, and Financial Customer Behaviour. Indeed, Rong *et al.* (2012) investigated the impact of electronic word-of-mouth (eWOM) on consumer behaviour within the tourism sector, employing an innovative association rule mining technique to scrutinize a dataset of outbound domestic tourism from Hong Kong. The study uncovered relationships between online experience sharers and users browsing travel websites, providing valuable insights for tourism managers to pinpoint target customers and improve their marketing strategies.

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The second topic that has not been extensively covered in the literature is the prediction of customers' variety-seeking behaviour. Tian *et al.* (2018) analyzed how various weather conditions, such as sunlight, temperature, and air quality, might be incorporated into marketing decision support systems (MDSs) to anticipate consumer behaviour, particularly their propensity for seeking variety in their purchases. The research indicated a notable correlation between weather conditions and an increase in variety-seeking behaviour, suggesting that weather data could be strategically used in data analytics to refine marketing approaches and increase profitability.

The last thematic gap is the domain of financial customer behaviour, which has been relatively neglected in research. Xiao (2012) underscored a potential gap in understanding the precise impact of these factors on marketing strategies of commercial banks and the efficacy of the proposed marketing strategy selection model. There is a call for a more in-depth analysis of how consumer behaviour influences marketing strategy selection, specifically within the context of commercial banking.

This analysis has identified certain limitations that could be instrumental in refining its outcomes and broadening its ability to address all facets of marketing strategy and various applications of artificial intelligence. One key limitation lies in the choice of keywords, where the focus solely on "marketing strategy" may overlook valuable insights that could be gleaned by incorporating additional relevant terms. For instance, expanding the scope to include terms like "market segmentation", "branding", "consumer behaviour", and "pricing strategy" could enrich the analysis. Similarly, within the realm of AI, considerations should extend beyond conventional methods to encompass hybrid techniques, generative models, and data analytics for a more comprehensive understanding. Furthermore, akin to any bibliometric study, this analysis did not conduct an examination of the intellectual structure through author and reference co-citations. The former facilitates the detection of clusters of researchers who have contributed to developing the pivotal themes within this literature, thereby offering insights into potential gaps. Similarly, the latter aids in identifying the concepts and theories upon which this literature has relied for its development. Collaborative cluster analysis by AI experts and marketing specialists can notably improve the bibliometric analysis of AI and strategic marketing literature. With AI specialists offering proficiency in cutting-edge data collection tools, market analysis techniques, and customer insights, the analysis gains from the forefront of technological progress. Concurrently, marketing specialists contribute insights into industry-specific requirements, ensuring the analysis is attuned to pertinent challenges. This synergy fosters a deeper comprehension of the interplay between AI and marketing strategies, augmenting the bibliometric analysis with actionable insights.

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Appendix A. Figures for the Study of AI and Marketing Strategy

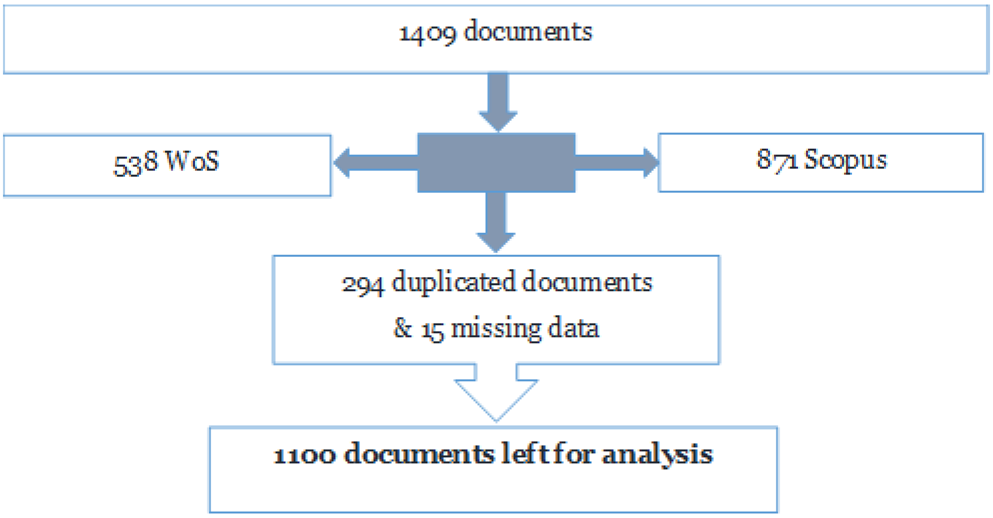

Figure 1. Summary of filtering data collection

Figure 2. Thematic factorial map

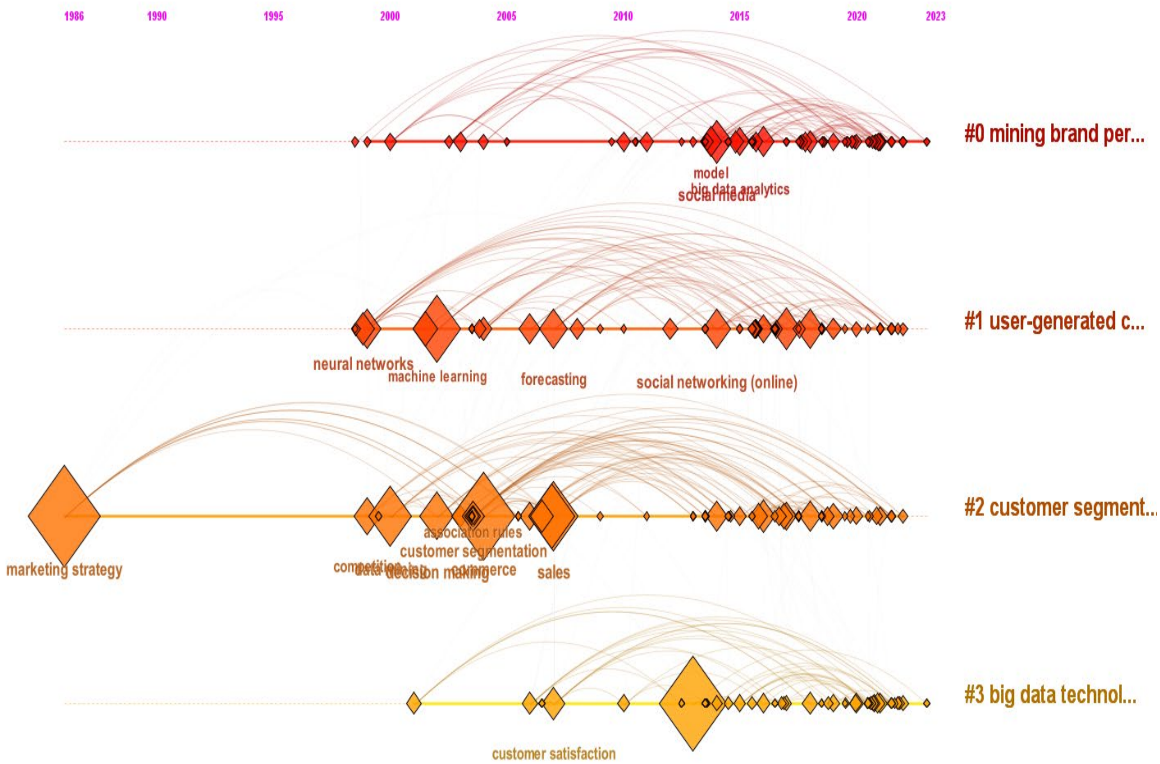

Figure 3. Visualization of keyword co-occurrence network

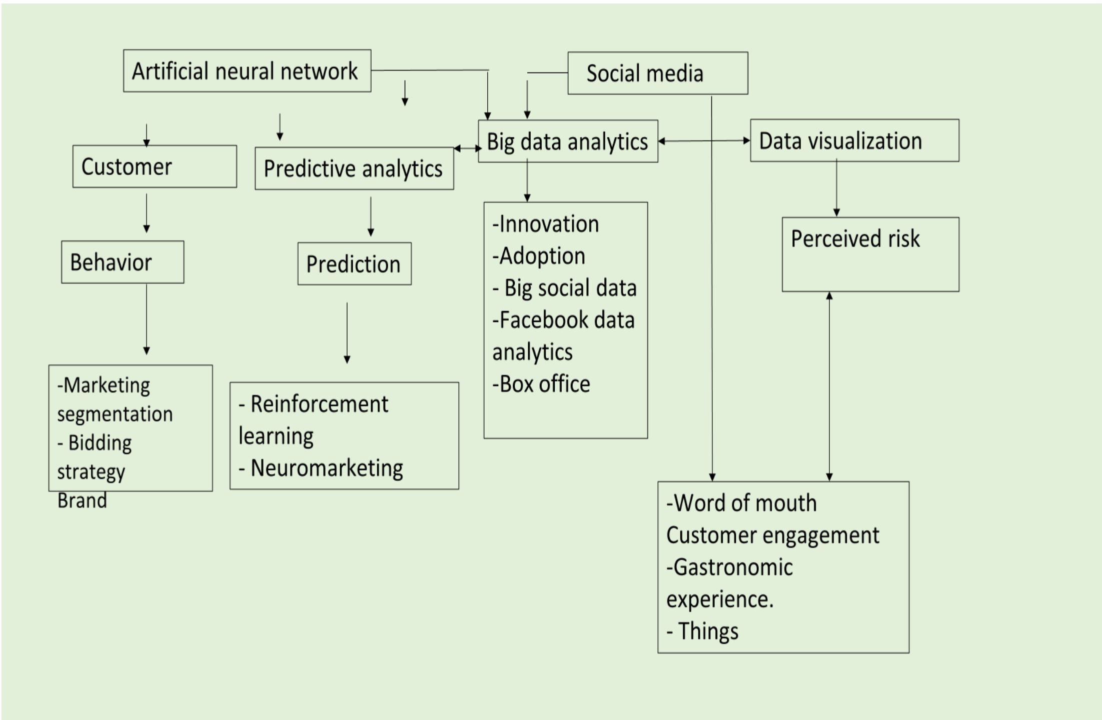

Figure 4. Cluster (#0) — the most important cluster

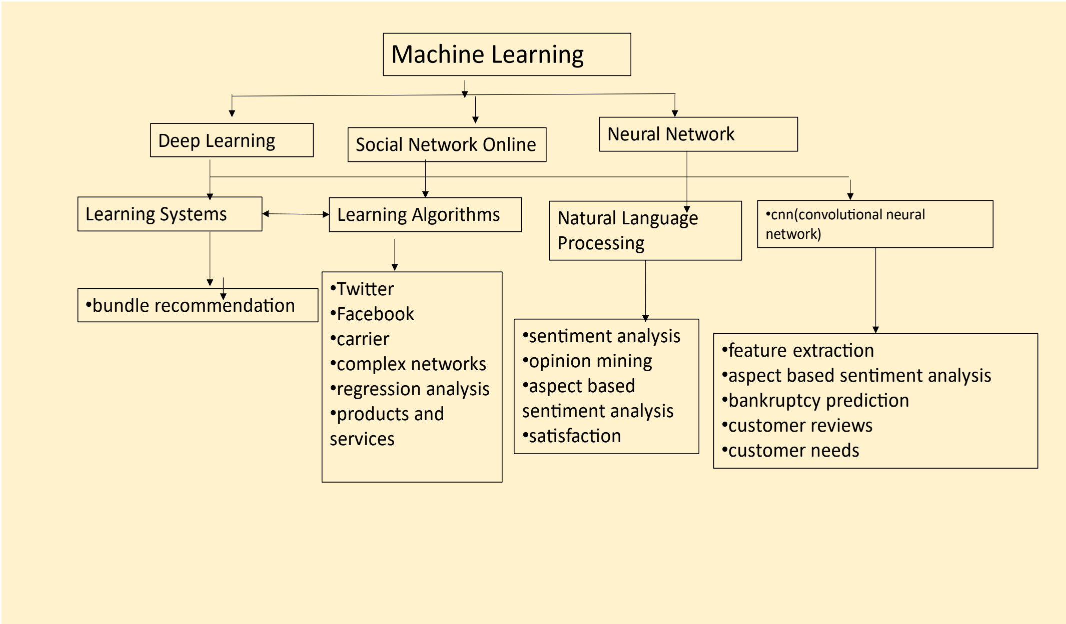

Figure 5. Cluster (#1) — the second most important cluster

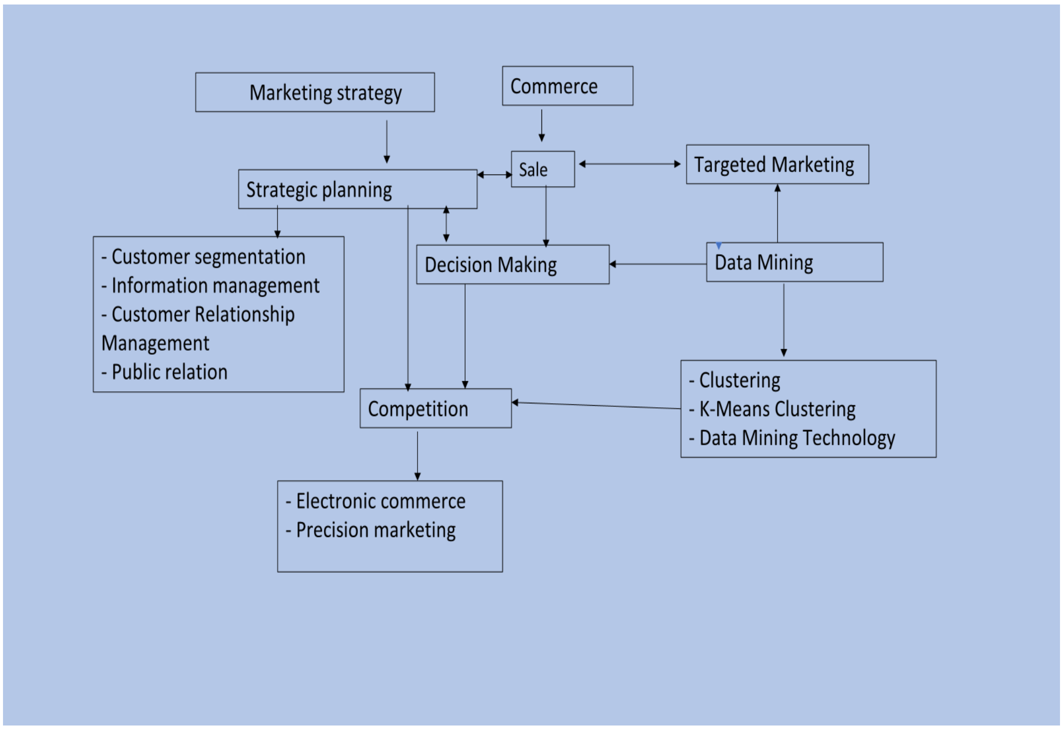

Figure 6. Cluster (#2) — the third most important cluster

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Appendix B. Topic Trends

Keywords	freq	year_q1	year_med	year_q3
fuzzy logic	7	2008	2011	2018
neural networks	20	2010	2016	2020
decision support system	11	2011	2016	2018
association rules	7	2014	2016	2020
social network	14	2015	2017	2019
business intelligence	11	2014	2017	2021
consumer behavior	8	2016	2018	2021
business analytics	5	2017	2018	2021
feature selection	5	2017	2018	2019
data mining	67	2016	2019	2021
internet of things	39	2019	2019	2021
customer segmentation	22	2016	2019	2020
big data	161	2018	2020	2021
marketing strategy	74	2018	2020	2021
marketing	65	2019	2020	2021
machine learning	119	2019	2021	2022
artificial intelligence	71	2020	2021	2022
digital marketing	47	2019	2021	2022
marketing management	11	2022	2022	2022
tourism	8	2022	2022	2022
covid-19	6	2022	2022	2022

Year_q1 (column 2): The year in which the topic was first highlighted by literature
Year_med (column 3): The median year
Year_q3 (column 4): The year in which the topic appeared most recently

Appendix C. AI and Marketing Strategy by Cluster

Table C1. Cluster (#0): Most cited documents

Author(s)	Marketing Strategy Analyzed	AI Tool Used	AI Tool Usefulness
Social media			
Culotta & Cutler (2016)	Mining Brand Perceptions	Data Mining (Twitter)	Effective for Inferring Attribute-Specific Brand Perception Ratings from Social Media (Twitter)
Steinhoff *et al.* (2018)	Online Relationship Marketing	Various Online Tools (E-commerce, Social media, Mobile, Big Data, AI, Augmented Reality)	Effective for Managing Customer Relationships Online and Informing Marketing Strategy
Ahani *et al.* (2019)	Market Segmentation in Spa Hotels	Machine Learning (Hybrid Algorithms)	Effective for Spa Hotel Segmentation and Travel Choice Prediction Using Online Reviews and Big Data from TripAdvisor

Author(s)	Marketing Strategy Analyzed	AI Tool Used	AI Tool Usefulness
Park *et al.* (2015)	Cruise Tourism Marketing	Twitter Data Analysis	Effective for Understanding Social Media Impact on Hospitality and Tourism, and Informing Marketing Strategies
Artificial neural network			
Ballestar *et al.* (2018)	E-commerce Social Network Marketing	Machine Learning (Predictive Model)	Effective for Predicting Customer Quality in E-commerce Social Networks and Personalizing Financial Incentives for Referral Marketing Strategies
Arya *et al.* (2021)	Social Networking Site Brand Communication	Artificial Neural Network, Smart-PLS, Process-macro	Effective in Understanding the Impact of Brand Communication on Consumer-Based Brand Equity (CBEQ) and the Role of Brand Attachment (BAT) as a Mediator on Social Networking Sites
Lyu & Choi (2020)	Organic Product Sales	Sentiment Analysis, Latent Dirichlet Allocation (LDA), Artificial Neural Network	Effective in Predicting Online Sales Volume and Identifying Key Factors for Selling Organic Products via Text Mining on Web Customer Reviews
Cuadros & Domínguez (2014)	Customer Segmentation	Self-Organizing Maps (SOM), Artificial Neural Network	Effective for Formulating Marketing Strategies Based on Customer Lifetime Value, Current Value, and Loyalty via Segmentation
Predictive Analytics			
Boldt *et al.* (2016)	Nike's Sales	Big Data Analytics, Facebook Data Analytics, Predictive Analytics, Regression Analysis	Effective for Forecasting Nike's Sales and Analyzing Activity on Nike's Facebook Pages
Dai & Wang (2021)	Social Media Marketing, Customer Engagement Behaviour	Machine Learning, Neural Network	Effective for Predicting Customer Engagement Behaviour in Response to Marketing Posts on Social Media Platforms
Prediction			
Abakouy *et al.* (2022)	Email Marketing Personalization	Machine Learning Models	Effective in Predicting Click Rates
Lakshmi *et al.* (2021)	Bitcoin Price Prediction	Various Machine Learning Models	Effective in Predicting Bitcoin Prices

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Author(s)	Marketing Strategy Analyzed	AI Tool Used	AI Tool Usefulness
Market segmentation			
Hsieh (2004)	Customer Behaviour Management	Integrated Data Mining and Behavioural Scoring Model	Effective in Customer Segmentation and Marketing Strategy Development
Ahani *et al.* (2019)	Spa Hotel Market Segmentation and Travel Choice Prediction	Machine Learning Approaches	Effective for Spa Hotel Segmentation and Travel Choice Prediction using Online Reviews and Social Big Data
Hanafizadeh & Mirzazadeh (2011)	Market Segmentation	Self-Organizing Maps (SOM) and Fuzzy Delphi Method	Effective for Visualizing Market Segmentation using Multiple AI Techniques

Table C2. Cluster (#2): Most cited documents

Author Name	Marketing Strategy Analyzed	AI Tool Used	AI Tool Usefulness
Strategic marketing			
Huang & Rust (2018)	Marketing Strategies	Mechanical AI, Thinking AI, Feeling AI	Useful for Strategic Marketing Planning
Kumar *et al.* (2021)	Various Marketing Strategies	Internet of Things, Artificial Intelligence, Machine Learning, Blockchain	Promising for Shaping Future Marketing Strategies
Thomaz *et al.* (2019)	Marketing in the Era of Hyper-Privacy	Conversational Agents (Chatbots)	Leveraging Chatbots to Enhance Personalization and Strategic Assets in Marketing
Trupthi *et al.* (2017)	Sentiment Analysis on Twitter	Streaming API	Improving Marketing Strategies with Real-Time Sentiment Analysis
Data mining			
Mahdiraji *et al.* (2019)	Digital Banking Strategy	Data Mining and Clustering (K-means), BWM, COPRAS	Developing a Digital Banking Strategy for Iranian Banks Based on Big Data Analysis
Garnier-Rizet *et al.* (2008)	Call Centre Conversational Speech	Automatic Transcription, Text Processing, Data Mining	Exploiting Conversational Speech for Detecting Major Events and Organizational Flaws, Improving Customer Relations and Marketing Strategies
Jabbar *et al.* (2019)	E-Commerce Product Reviews	Support Vector Machine (SVM)	Improving Marketing Strategies through Real-time Sentiment Analysis on E-Commerce Product Reviews

Author Name	**Marketing Strategy Analyzed**	**AI Tool Used**	**AI Tool Usefulness**
Commerce			
Tong *et al.* (2019)	Mobile Marketing	Artificial Intelligence (AI)	Enhancing Mobile Marketing Strategies through Personalization
Zhao *et al.* (2019)	Marketing Machine Learning	Feature Selection with mRMR (Minimum Redundancy and Maximum Relevance)	Enhancing Feature Selection in Marketing Machine Learning Platforms
Ducange *et al.* (2017)	Marketing Strategies	Big Data Analytics	Leveraging Big Data Analytics for Marketing
Strategic planning			
Yoseph & Heikkila (2018)	Retail Customer Segmentation	Enhanced RFM and Hybrid Regression/Clustering	Clustering methods to segment retail customers, allowing retailers to focus on profitable customers and make informed decisions.
Egebjerg *et al.* (2017)	Football Spectator and TV Ratings Prediction	Big Social Data Analytics	Predicting spectators and TV ratings in football.
Amin *et al.* (2020)	Consumer Behaviour Analysis in Neuromarketing	Data Mining and Machine Learning	Enriching marketing with EEG-based consumer insights (95%)
CRM			
Chatterjee *et al.* (2021)	B2B Relationship Management	AI-Based CRM (AI-CRM)	AI-CRM impact on B2B performance and advantage.
Salehinejad & Rahnamayan (2016)	Customer Behaviour Prediction	Recurrent Neural Networks (RNNs)	RNNs predict RFM values for personalized marketing with high efficiency.
Hung *et al.* (2019)	Customer Segmentation	Hierarchical Agglomerative Clustering	A machine learning hierarchical agglomerative clustering (HAC) algorithm to perform customer segmentation on credit card datasets.
Oztekin (2017)	Marketing Strategy in Healthcare Industry	Data Analytics (Support Vector Machines, Artificial Neural Networks, Decision Trees)	Utilizing data analytics, including support vector machines, neural networks, and decision trees, enhances marketing managers' event location selection and market analysis, optimizing marketing strategies.

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Author Name	Marketing Strategy Analyzed	AI Tool Used	AI Tool Usefulness
Bhade *et al.* (2018)	Customer Segmentation and Buyer Targeting	K-Means Clustering, Singular Value Decomposition	Leveraging K-Means clustering and Singular Value Decomposition enhance profitability through retail customer segmentation, targeting, and overcoming recommender system challenges.
Customer segmentation			
Wang *et al.* (2020)	Customer Patterns in Supply Chain	Big Data Analytics, RFM, K-means, Naive Bayes, Linked Bloom Filters	Useful for Marketing Strategies and Predicting Customer Demands
Wang *et al.* (2014)	User Behaviours in Mobile Networks	Data Mining, Fuzzy C-means Clustering	Useful for Understanding User Behaviours and Informing Marketing Strategies
Hung *et al.* (2019)	Customer Segmentation	Hierarchical Agglomerative Clustering (ML)	Useful for Designing Marketing Strategies based on Customer Segmentation
Tupikovskaja-Omovie & Tyler (2020)	Consumer Segmentation	Mobile Eye-Tracking Technology	Useful for Developing Personalized Shopping Experiences on Smartphones
Yang *et al.* (2016)	Consumer Shopping Behaviour	Mobile Eye-Tracking Technology	Valuable for Retailers' Digital Marketing Strategy and Artificial Intelligence Systems

An Empirical Study of the Impact of Social Media Data Analytics on Marketing Strategy

Which Social Media Data Analytics Metrics to Select?

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Abstract: Social Media Data Analytics (SMDA) has emerged as a dynamic and growing field across various disciplines, including marketing. However, practitioners and researchers in the marketing domain have realized that harnessing the full potential of SMDA for guiding marketing strategies necessitates a clear understanding of the relevant SMDA metrics. A significant challenge lies in the lack of clear guidance on which SMDA metrics are most relevant for enhancing marketing strategies. This study aims to empirically evaluate the impact of SMDA on marketing strategies. To achieve this goal, the study carried out a questionnaire for data collection and employs an empirical investigation using the PLS-SEM methodology. The results show that the impact of SMDA on marketing strategy depends on SMDA metrics (data type, platforms and analysis methods) and also on marketing strategy type. The results suggest a valid conceptual model introducing novel metrics for the SMDA concept. These results present a broader perspective on how SMDA affects marketing strategies and suggest that future research should focus on a specific type of marketing strategy and study SMDA metrics in a different and more in-depth way.

Keywords: Social Media Data Analytics (SMDA), Marketing Strategies, Conceptual framework, Empirical study, PLS-SEM.

Introduction

The extensive usage of social media in our daily lives has resulted in the creation of large amounts of unstructured data (Stieglitz *et al.*, 2018). This data, gathered from social media platforms, is of value to analysts and specialists who aim to monitor and analyze various indicators related to business performance. Recently, the field of Social Media Data Analytics (SMDA) has emerged as a dynamic area spanning various disciplines, including marketing (Kaabi & Jallouli, 2019; Lee, 2018; Misirlis & Vlachopoulou, 2018). SMDA refers to the practice of collecting and analyzing social media data to assist decision-makers in addressing specific issues (Lee, 2018). The SMDA concept is built on Claude Shannon and Warren Weaver's Information Theory, which explores the utilization of information within a specific context (Ritchie, 1986). According to Misirlis & Vlachopoulou (2018), SMDA holds the potential to reshape marketing strategies within organizations and companies. However, realizing these opportunities requires both practitioners and researchers to increasingly examine data originating from social media platforms (Stieglitz *et al.*, 2018).

To effectively utilize this data for marketing insights, it is crucial to understand how to choose appropriate metrics and dimensions for SMDA (Misirlis & Vlachopoulou, 2018). Many researchers have explored the link between SMDA and marketing strategies, advocating for deeper investigation into different aspects of this relationship (Lee, 2018; Misirlis & Vlachopoulou, 2018; Rowley & Keegan, 2020). Earlier studies have also prompted a more detailed exploration of this relation by focusing on specific metrics (like data types, analysis methods, data sources, etc.) and emphasizing the need to choose suitable measurement scales to precisely outline the various dimensions of this connection (Campbell *et al.*, 2020; Stieglitz *et al.*, 2018; Saggi & Jain, 2018).

Consequently, there remains uncertainty in the literature regarding the selection of the most suitable metrics to guide marketing strategy. Furthermore, despite the increasing number of publications utilizing SMDA in the marketing field, there is a lack of comprehensive conceptual frameworks that thoroughly explore the process of using SMDA for marketing strategies (Lee, 2018; Stieglitz *et al.*, 2018; Saggi & Jain, 2018; Campbell *et al.*, 2020).

To bridge this gap, this article aims to empirically estimate the impact of SMDA on the marketing strategy concept. To do this, this research reports the results of a survey carried out to test the proposed model. PLS-SEM was used to analyse the data.

This study intends to assist both marketing researchers and practitioners by generating a guide, an overview, and a mapping that addresses the impact of SMDA and its metrics on various types of marketing strategies. Thus, the research questions of this research are:

- To what extent does the process of SMDA ensure benefits for marketing strategies?
- Which metric of SMDA guides marketing strategies?

The paper is organized as follows. The first section is intended to explore the literature related to marketing strategies and SMDA. The second section serves to introduce, drawing on the literature, a conceptual model that elucidates the relationship between the two concepts, SMDA and marketing strategy, along with their key dimensions. The third section outlines the methodology employed in the empirical study. The fourth section presents and discusses the main results of the data analysis process. Finally, the fifth section encompasses a concise

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conclusion, acknowledges limitations, and provides recommendations for prospective research endeavours.

Literature Review: SMDA to Guide Marketing Strategies

To investigate the impact of SMDA on marketing activities, Moe & Schweidel (2017) introduced a theoretical framework treating SMDA as a source of marketing information. Similarly, Misirlis & Vlachopoulou (2018) conducted theoretical research on SMDA metrics in the marketing domain, proposing that companies capable of gauging and harnessing the hidden potential of big data from social media could acquire insights to optimize product and service promotions, enhance targeting, foster brand loyalty, and elevate other marketing performance indicators. Considering intelligent tourism destinations, Vecchio et al. (2018) demonstrated what Social Big Data can bring to the value creation process. Verhoef & Bijmolt (2019) formulated a conceptual framework detailing how digital models and technologies influence markets and business performance. Likewise, Campbell et al. (2020) elucidated how the application of AI technology can enhance marketing planning and strategic approaches. By focusing on market performance, Gupta et al. (2020) endeavoured to explore the relation between big data predictive analytics and organizational performance. Benslama & Jallouli (2022) proposed a theoretical framework, through a systematic literature review of 120 articles published from 2015 to 2021, to delve into how SMDA can steer marketing strategies.

Conceptual Framework

The referenced articles in the preceding section are fundamentally grounded in 'Information Theory', pioneered by Claude Shannon and Warren Weaver, delving into the use of information within a specific context (Ritchie, 1986). Furthermore, they evidence how an organization's internal operations pinpoint avenues for value creation, aligned with Michael Porter's Value Chain Theory (Porter, 1985).

Based on the studies discussed in the previous section, it can be expected that SMDA use can exert a positive impact on marketing strategies. Moreover, the in-depth study of the literature suggests that the dimensions and metrics of SMDA are not yet well studied by researchers nor tested empirically (Misirlis & Vlachopoulou, 2018; Benslama & Jallouli, 2022; Ramadeen & Oosterwyk, 2023).

According to Misirlis & Vlachopoulou (2018), in the field of marketing, the SMDA process is significantly impacted by two main dimensions: SMDA methods and social media platforms. Lee (2018) provided an overview of SMDA adoption for businesses, and highlighted the importance of the SMDA method, platforms, and data type. SMDA method, social media platform, and data type have also appeared in many studies as SMDA metrics (Batrinca &

Treleaven, 2015; Ghani *et al.*, 2019; Galetsi *et al.* , 2020). Therefore, SMDA relies on three main metrics: methods, platforms, and data type.

On the other hand, among the most important indicators contributing to the success of a marketing strategy is "the effectiveness" (DeLone & McLean, 1992). This indicator can be defined by the extent to which a strategy achieves the predefined objectives (Dean & Sharfman, 1996). Effectiveness is widely used by researchers and can be adapted depending on the context and the used concept (Wang & Byrd, 2017; Shamim *et al.*, 2019). Shamim et al. (2019) suggest that Big Data enables companies to improve the effectiveness of business strategies. In light of these arguments, this study proposes that the use of SMDA has a positive impact on the effectiveness of marketing strategy. Thus, the following hypothesis is proposed:

H1: SMDA has a positive impact on marketing strategy.

Moreover, regarding the marketing strategy concept, Benslama & Jallouli (2022) established a theoretical framework encompassing five primary strategies inspired by Leonidou et al. (2002), Armstrong et al. (2014), and Campbell et al. (2020), namely: Targeting and Positioning Strategy; Product, Service and Brand Strategy; Communication and Influence Strategy; Pricing Strategy; and Channel and Logistics Strategy.

Thus, this research considers that marketing strategy is reflected by six dimensions (Figure1). The linking of all the SMDA and marketing strategy dimensions leads to schematize the conceptual model shown in Figure 1.

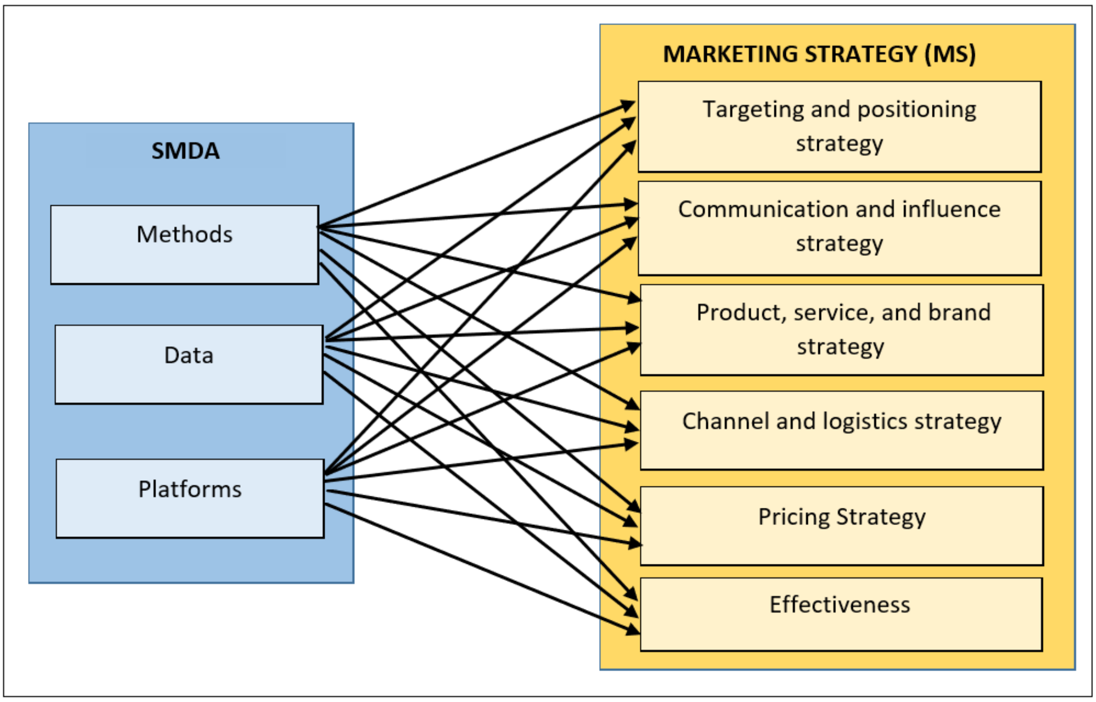

Figure 1. The conceptual model of the impact of Social Media Data Analytics on Marketing Strategies

Methodology

The relations and hypotheses presented in our conceptual model are drawn from existing literature. This study seeks to empirically validate these relations, so this study follows a positivist epistemology that favours the application of quantitative methods to test causal relationships (Creswell, 2003).

Given the absence of geographical boundaries in our study, we opted for online questionnaire dissemination (via email, Facebook, Messenger, LinkedIn). Google Forms was adopted due to its cost-effectiveness and practicality for information collection (Bhattacherjee, 2012).

We employed a convenience sampling method, due to the limited nature of our targeted population (professionals knowledgeable in both SMDA and marketing strategy). The measurement scales were identified based on previous research. Tables A1 and A2 in the Appendix provide a summary of the main measurement scales, items and sources for SMDA and Marketing Strategy variables that were included in the questionnaire (such as Blankson & Kalafatis (2004); Filipe Lages et al. (2008); and Slater & Olson (2001)).

To ensure questionnaire clarity, a pretest was conducted involving a small subset of targeted individuals to gather their feedback (Jolibert & Jourdan, 2011). To this end, our questionnaire was distributed to 30 individuals. This pretest facilitated the incorporation of valuable insights (for instance, four respondents recommended adding the LinkedIn platform due to its perceived professional significance).

The questionnaire was distributed to 600 professionals, resulting in 317 collected responses, of which only 132 reported the utilization of SMDA in their enterprises. It is worth noting that the questionnaire was launched on December 20, 2021, and concluded on July 4, 2022.

The descriptive analysis of our sample reveals that most of the surveyed businesses are small and medium-sized enterprises (63.5%). Respondents primarily belong to the following departments within their companies: the IT department (39.4%); marketing department (11%); and production department (10.1%). Most companies in our sample are located in Tunisia (61.5%), followed by France (18%) and Mexico (7.6%). Regarding the sectors of these businesses, the predominant ones are technology (37.8%), automotive industry (11.2%), and education/culture (7.4%).

Following data collection and descriptive analysis, we proceeded to the application of statistical tests to evaluate the validity of our proposed model and to test the reliability of the variables, dimensions, and measurement instruments. The data analysis process consists of two basic steps: the first step involves exploratory factor analysis, while the second step aims to test the relationships between variables and examine the study's structural model.

For the exploratory factor analysis, we started by determining the main factors of each variable. We thus applied the Principal Component Analysis method (PCA), which represents the most commonly used method (Carricano *et al.*, 2010). Then, we assessed reliability to examine the internal consistency of measurement scales by using "Cronbach's Alpha".

To evaluate the model's validity, we employed the Structural Equation Modelling (SEM) method. Specifically, we applied the Partial Least Squares-SEM (PLS-SEM) method. The PLS-SEM, renowned for its capacity to address various research types (confirmatory, predictive, exploratory, etc.) (Benitez et al., 2019), and its robustness in dealing with non-normally distributed data, demonstrates its effectiveness, even when applied to small sample sizes, as in our specific case (Hair *et al.*, 2011).

Main results and Discussion

Exploratory factor analysis of the SMDA variable

The proposed conceptual model breaks down the SMDA variable into three factors: "Data", "Methods" and "Platforms". These three factors encompass a total of 21 items. To conduct factor analysis on the SMDA variable, we performed PCA on all 21 items. The KMO test produced a value of 0.853, which is considered excellent and indicates that the data can be factored (Pett *et al.*, 2003).

The PCA with Varimax rotation generated six factors, ensuring a good representation quality for all the items (with loadings >0.5) (Evrard *et al.*, 2009) and capturing 74.5% of the total variance.

In our conceptual model, the SMDA variable encompasses three factors. Based on the PCA results, only the "Methods" factor is retained. For the other two factors, Varimax rotation classified them into sub-factors: "Data" was divided into two sub-factors, the first encompassing three data types — text, image, and video — while the second included likes, comments, hashtags, and ratings. Regarding the "Platforms" factor, it was divided into three dimensions: the first comprised Twitter, Facebook, and Instagram; the second encompassed YouTube and LinkedIn; and the third included platforms like TripAdvisor, Yelp, Weibo, and Booking that pertain to specific domains, activities, or subjects. As such, we replaced the three factors from our conceptual model with the six factors from the PCA results, since we found this arrangement meaningful and useful. Thus, the "Methods" factor remains unchanged; the "Data" factor resulted in two distinct dimensions. "General Data" (composed of three items) and "Specific Data" (composed of three items). The "Platforms" factor yielded three different dimensions, which we named "General Platforms" (composed of three items), "Specific Platforms" (composed of four items) and "Professional Platforms" (composed of two items).

We considered YouTube as a professional platform, since the majority of its users are liberal professionals (artists, businesses, educators, etc.) (Firat, 2019; Costa-Sánchez, 2017).

The Cronbach's alpha of the overall SMDA variable was estimated, yielding a reliable value surpassing the empirical threshold (0.894), with acceptable correlations (> 0.3) (Zalma *et al.*, 2015) among the elements of this variable. In a second step, we proceeded with the reliability analysis for each SMDA dimension separately. The results displayed in Table 1 demonstrate that internal consistency reliability is maintained for all dimensions (>0,6) (Evrard *et al.*, 2009).

Table 1. Internal consistency test for the SMDA variable

Dimension	Cronbach's alpha	Average correlation (r)
General Data (GD)	0.795	0.569
Specific Data (SD)	0.819	0.599
General Platforms (GPL)	0.664	0.40
Specific Platforms (SPL)	0.919	0.746
Professional Platforms (PPL)	0.648	0.480
Methods (METH)	0.862	0.512
The global variable: SMDA	**0.894**	**>0.3**

Exploratory factor analysis of the Marketing Strategy variable

The PCA with six factors without rotation displayed a good representation quality for all items and indicated that both the KMO test and the Bartlett's test of sphericity (p=0.000) are significant for the marketing strategy variable. Moreover, the results showed the absence of multicollinearity with a non-zero determinant (2.127E-023) and demonstrated acceptable correlations between items.

Moving forward to the application of PCA with rotations, we obtained a relevant structure identical to our conceptual model with six factors. Varimax rotation described 70.8% of the explained total variance; and produced a KMO test value of 0.918; a significant Bartlett's sphericity test (p=0.000); a non-zero determinant; and a good quality of representation and factor contributions for all items.

Factor F1 included four items corresponding to the "Effectiveness" dimension. The second factor, F2, consisted of 14 items related to the "Targeting and Positioning Strategy" dimension. The third factor, F3, encompassed nine items describing the "Communication and Influence Strategy" dimension. The fourth factor, F4, referred to the "Product, Service, and Brand Strategy" dimension with its eight items. The fifth factor, F5, related to the "Channel and Logistics Strategy" dimension with five items. Finally, the sixth factor, F6, included six items describing the "Pricing Strategy" dimension.

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The internal consistency is ensured for all factors as well as for the global variable "Marketing Strategy", as the application of the reliability test on this scale yields an excellent Cronbach's alpha value (0.970) and an average correlation among elements of 0.410 (Table 2).

Table 2. Internal consistency test for the Marketing Strategy variable

Dimension	Cronbach's alpha	Average correlation (r)
Effectiveness (EFF)	0.921	0.746
Targeting and Positioning Strategy (TPS)	0.952	0.606
Communication and Influence Strategy (CIS)	0.934	0.614
Product, Service, and Brand Strategy (PSBS)	0.926	0.584
Channel and Logistics Strategy (CLS)	0.898	0.638
Pricing Strategy (PS)	0.922	0.664
The global variable: Marketing Strategy	**0.970**	**0.410**

PLS-SEM method: model testing and validation

The measurement reliability analysis reveals that both Twitter and Sentiment Analysis indicators exhibited low loadings (<0.7), which affected their constructs' reliability; therefore, we removed these two items (Hair *et al.*, 2011). After removing Twitter and Sentiment Analysis, the results indicate that the correlations between the indicators and their constructs exceed (or are close to) the threshold of 0.7 (Henseler *et al.*, 2009), ensuring indicator reliability.

Table A3 in the Appendix shows that the Cronbach's α values are acceptable (> ≈0.6), and the obtained values for composite reliability and Rho (A) adhere to the recommended threshold of 0.7.

The results indicate that the AVE (Average Variance Extracted) for each construct meets the required threshold (AVE > 0.5 as per Fornell & Larcker (1981)). This implies that convergent validity is ensured. Using the HTMT (Heterotrait-Monotrait) method, all HTMT correlation values are below the threshold of 0.85 (Henseler *et al.*, 2015), demonstrating that discriminant validity is confirmed.

To validate the structural model, we began by checking for multicollinearity issues: all VIF (Variance Inflation Factor) values were found to be below 5 for each construct, indicating no multicollinearity issues (Akter *et al.*, 2016). We then proceeded to estimate the effect size f^2 and the coefficient β to assess the significance of relationships in the internal model using the Bootstrapping PLS-SEM algorithm (Hair *et al.*, 2017). The results show that twelve relationships are significant at the 0.05 threshold and have an acceptable effect size f^2 (>0.02) (Figure 2).

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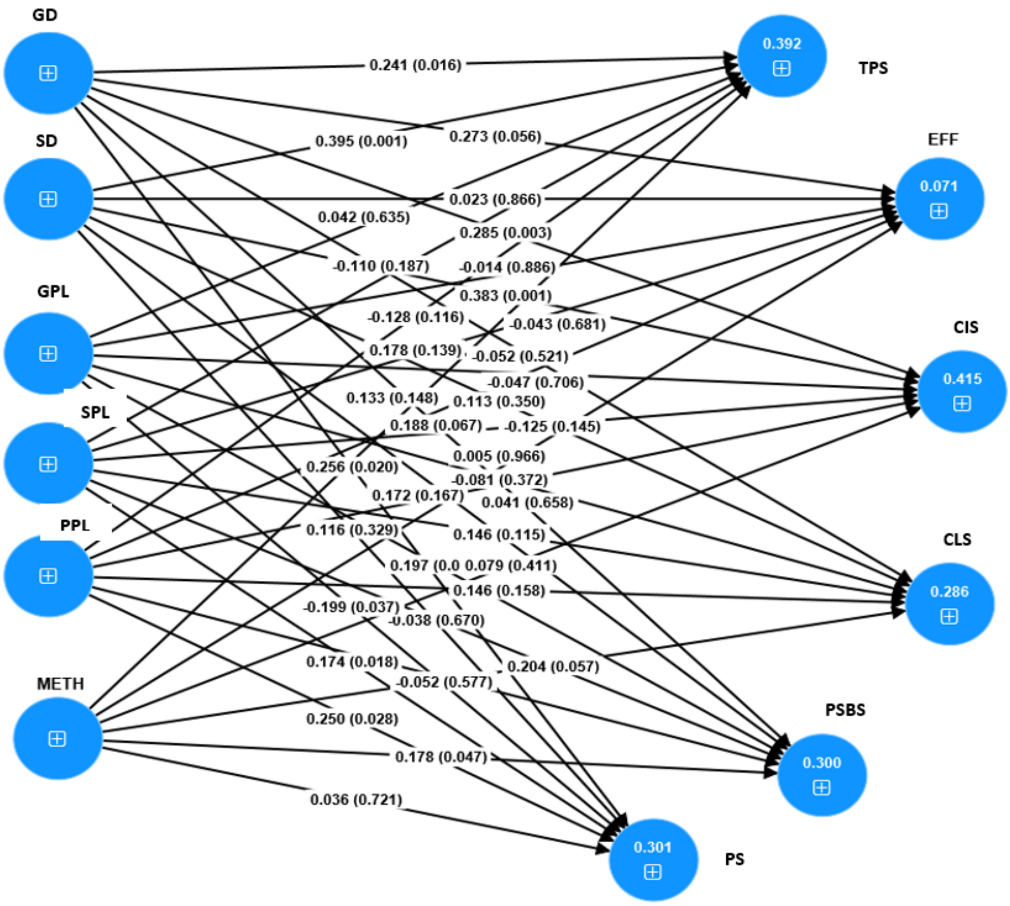

Figure 2. Internal model estimation

The predictive and explanatory power of the model can be assessed through two coefficients, R^2 and Q^2 (Hair *et al.*, 2017). Table 3 shows that all R^2 values obtained are acceptable as they exceed 0.1 (Falk & Miller, 1992). These values suggest that the model is primarily explained by "Communication and Influence Strategy" and "Targeting and Positioning Strategy", and that the explanatory power of our structural model is moderate and acceptable (Chin, 1998). By examining the Q^2 coefficient, we can assess the predictive power of each construct (Table 3). A positive Q^2 value indicates that the predictive relevance of the construct is confirmed (Geisser, 1974; Stone, 1974). Note that the highest predictive relevance is presented for the dimensions "Communication and Influence Strategy" and "Targeting and Positioning Strategy". Furthermore, the results showed the absence of predictive relevance for the "Effectiveness" dimension.

Table 3. R^2 and Q^2 coefficients generated by the PLS-SEM algorithm

	R-squared	Q²predict	Results
Effectiveness	0.109	-0.034	no predictive relevance
Communication and Influence Strategy	0.513	0.345	strong predictive relevance
Channel and Logistics Strategy	0.353	0.193	moderate predictive relevance
Targeting and Positioning Strategy	0.503	0.321	strong predictive relevance

	R-squared	Q²predict	Results
Pricing Strategy	0.402	0.216	moderate predictive relevance
Product, Service, and Brand Strategy	0.359	0.214	moderate predictive relevance

On the basis of all statistical analysis results presented above (exploratory factor analysis, external and internal model assessment), the final structure of our model is shown in Figure 3.

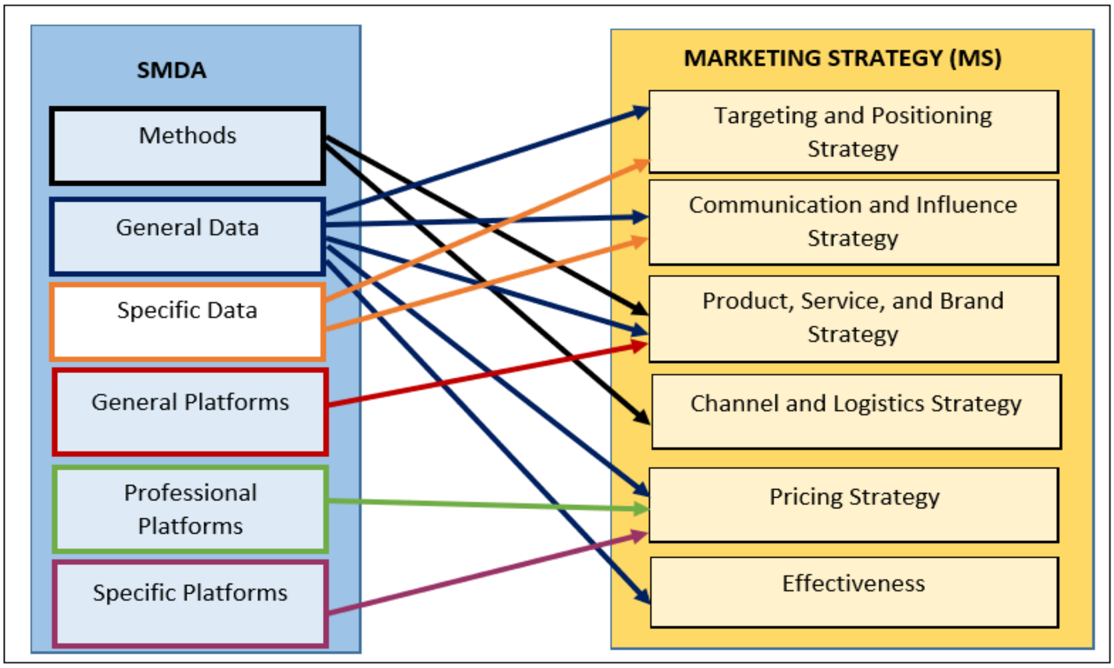

Figure 3. Impact of SMDA metrics on marketing strategies (framework with confirmed hypotheses)

The conceptual model evaluation, using SMART-PLS-4, with the new metrics derived from the exploratory factor analysis demonstrated that SMDA has a partial positive impact on marketing strategy. Moreover, the empirical study showed that the use of text, image, and video data in SMDA has a positive impact on all marketing strategies (except Channel and Logistics Strategy) and also on Marketing Strategy Effectiveness. In contrast, the use of data types, such as hashtags, ratings, number of likes, and comments, has a direct positive impact only on Targeting and Positioning Strategy and Communication and Influence Strategy. Additionally, the empirical results revealed that analyzing platforms like Facebook and Instagram can positively influence Product, Service, and Brand Strategy, while analyzing platforms like LinkedIn, YouTube, Tripadvisor, Yelp, Weibo, and Booking can guide Pricing Strategy. The results also demonstrated that adopting methods, such as statistics, artificial intelligence, coding and modelling, data mining, and/or visualization, in the SMDA process can yield several advantages for Channel and Logistics Strategy and Product, Service, and Brand Strategy.

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Furthermore, the evaluation of the structural model using the Bootstrapping algorithm confirmed that, among all dimensions of SMDA, Specific Data (hashtags, ratings, the number of likes, comments, etc.) are the most likely to positively influence Targeting and Positioning Strategy and Communication and Influence Strategy. Thus, analyzing Specific Data is recommended for the development of these two strategies. The second dimension of SMDA that has a strong impact on both Targeting and Positioning Strategy and Communication and Influence Strategy is the "General Data" dimension, which encompasses textual data, images, and videos. Therefore, we can generally consider the primary SMDA metric that practitioners should focus on to guide these two types of strategies is the type of data to analyze.

Additionally, the test of the explanatory and predictive power of the global model demonstrated that the model is primarily explained by Targeting and Positioning Strategy and Communication and Influence Strategy, which also exhibited strong predictive relevance. followed by Pricing Strategy, Product, Service, and Brand Strategy, Channel and Logistics Strategy, and, finally, the Effectiveness variable with a low R^2 value of 0.109. This indicates that Targeting and Positioning Strategy and Communication and Influence Strategy are more influenced by SMDA than other types of strategies.

Results also show that SMDA has a very weak positive impact on strategy effectiveness, and also indicate the absence of predictive relevance for the "Effectiveness" dimension. This result can be explained by the early stage of SMDA adoption (the majority of companies that participated in the survey indicated that they had started adopting SMDA technology within the last two to five years). Indeed, SMDA technologies require experimentation time to implement suitable analysis strategies that can improve the effectiveness of marketing strategies (Jabado & Jallouli, 2023).

It should be Highlighted that the measurement reliability analysis obtained using SMART-PLS led to eliminating the Twitter platform and the Sentiment Analysis method from the analysis due to their low saturation. It is possible that the weak correlation between the "Twitter" indicator and its "General Platforms" construct goes back to the lack of resemblance of Twitter to the two platforms Facebook and Instagram (remembering that Instagram belongs to the Facebook company). For example, posts on Facebook and Instagram are unlimited and permanent. Conversely, with Twitter posts limited to 140 characters, the lifespan of posts is very short and the functions are also limited (Surbhi, 2017). Regarding the "Sentiment Analysis" method, its low saturation may be due to the presence of the Artificial Intelligence method among the analysis methods, since many analysts consider Sentiment Analysis to be just a tool, or a special case, of Artificial Intelligence that works with Natural Language Processing to provide sentiment-based knowledge (Lee, 2018).

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Conclusion, Implications and Perspectives

This study aimed to propose a reliable conceptual model through empirical evidence concerning the relation between SMDA and marketing strategy. To the best of our knowledge, this study is the first to provide empirical evidence regarding the impact of SMDA and its dimensions on various marketing strategies.

The exploratory analysis conducted in this study validated the reliability of the following six dimensions for marketing strategy: Targeting and Positioning Strategy; Product, Service, and Brand Strategy; Pricing Strategy; Channel and Logistics Strategy; Communication and Influence Strategy; and Effectiveness (Armstrong *et al.*, 2014; Campbell *et al.*, 2020; Shamim *et al.*, 2019). It also confirmed the reliability of considering the following six dimensions of SMDA: Methods, General Data, Specific Data, General Platforms, Specific Platforms, and Professional Platforms. This classification allowed for distinguishing between different types of data and platforms, emphasizing that social media data and platforms should not be treated as a homogeneous group. Instead, adapting approaches to each group can enhance the expected marketing analysis outcomes.

This research explored the relationship between SMDA and marketing strategy, developing an empirical model that positions SMDA as a key driver of value creation for companies in shaping their marketing strategies. Furthermore, the empirical study supported the reliability and validity of the proposed framework.

In summary, based on all the results of the empirical analysis, we can conclude that SMDA does not always guarantee improvement in marketing strategy. It is essential to carefully select, depending on the nature of the marketing strategy to be developed, the most appropriate SMDA metrics (platform type, method, and data type). For example, the results showed that analyzing Professional Platforms is more suitable for guiding Pricing Strategy than analyzing General Platforms. Thus, it is crucial to specify the most important metric to focus on before starting the analysis. Results also show that the Channel and Logistics Strategy is only impacted by the use of analysis methods, so practitioners should give higher importance to the choice of analysis method rather than other metrics or dimensions.

This article represents a significant advancement in Value Chain Theory and information theory by shedding light on how SMDA metrics affect marketing strategies, and by defining six key metrics of SMDA applied to marketing strategies. By detailing these metrics, the article provides an essential conceptual framework for comprehending and measuring the impact of SMDA metrics on strategic marketing decisions.

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The originality of this research lies in addressing the literature and industry's need for a comprehensive, reliable, global, and valid conceptual framework to guide both researchers and practitioners in the SMDA process for developing marketing strategies. Furthermore, this study provides numerous reliable measurement scales adopted and used for the first time in a context different from their original design.

Regarding the practical contribution of this research, it presents and discusses various SMDA solutions, aiding decision-makers in selecting the right combination of different SMDA components and metrics based on their marketing requirements and needs to extract insights for their marketing strategies. Thus, based on this study, marketing researchers and practitioners can quickly select the most suitable social media platform, data type, and analysis method. Moreover, this research has provided results that offer a roadmap for describing the relationships between research concepts in a comprehensive way, likely to inspire researchers and practitioners to explore and experiment with different possible combinations of social media platforms, data types, and analysis methods, depending on the targeted marketing strategies, within specific industries through surveys, case studies and qualitative research.

This study has thus addressed the call made by Misirlis & Vlachopoulou (2018) and Jallouli & Kaabi (2022) highlighting the need for a conceptual framework encompassing social media, analytics, and marketing. Furthermore, it contributes to the enhancement of prior research efforts (such as Stieglitz *et al.*, 2018 and Galetsi *et al.*, 2020) aimed at providing a more thorough explanation and understanding of the SMDA process and its impact on marketing strategy. Unlike previous studies that focused on specific industry domains, single data types, or particular platforms/methods of analysis (such as Benslama & Jallouli, 2020 and Chebil *et al.*, 2021), this study explored a large set of SMDA metrics, offering insights into the SMDA framework for marketing strategies.

Finally, this study has certain limitations, including the small sample size in the questionnaire. It is highly recommended to conduct a study with a larger sample size for more robust results. Additionally, the research model treats the research concepts in a general and global manner, and tests only direct effects. To enhance the depth of understanding, it would be beneficial to explore the subject in more specific contexts and incorporate other mediating or moderating variables, a consideration for future research endeavours.

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Appendix

Table A1. SMDA variable measurement scales

Dimension	ITEMS	SOURCE
Platforms	Twitter Facebook Instagram TripAdvisor YouTube Yelp Weibo Booking LinkedIn	Choudhury & Harrigan (2014); Benslama & Jallouli (2022)
Data	Text Image Video Number of (likes, comments, etc.) Hashtags Rating	Gupta & George (2016); Vitari & Raguseo (2020); Benslama & Jallouli (2022)
Methods	Sentiment analysis Artificial intelligence Data mining Statistical Visualization Coding and modelling	Gupta & George (2016); Vitari & Raguseo (2020); Benslama & Jallouli (2022)

Table A2. Marketing strategy variable measurement scales

Measurement scale of the Targeting and Positioning strategy	
ITEM	**SOURCE**
Top of the range, product/service range	Blankson & Kalafatis (2004)
Reliability	Blankson & Kalafatis (2004)
Attractiveness	Blankson & Kalafatis (2004)
Country of origin	Blankson & Kalafatis (2004)
Product positioning	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Market segmentation	Slater & Olson (2001); Benslama & Jallouli (2022)
Evaluate which market to target	Slater & Olson (2001); Benslama & Jallouli (2022)
Focus on specific segments	Slater & Olson (2001); Benslama & Jallouli (2022)
Search for customer information	Al-Surmi *et al.* (2020); Olson *et al.* (2005); Narver & Slater (1990); Benslama & Jallouli (2022)
Customize offers	Jayachandran *et al.* (2005); Benslama & Jallouli (2022)
Identify your best customers	Jayachandran *et al.* (2005); Benslama & Jallouli (2022)
Analyze competitive advantages/disadvantages	Al-Surmi *et al.* (2020); Olson *et al.* (2005); Narver & Slater (1990); Benslama & Jallouli (2022)
Increase consumer engagement, satisfaction and retention	Cao *et al.* (2019); Benslama & Jallouli (2022)
Attract new customers and sales	Slater & Olson (2001); Benslama & Jallouli (2022)
Measurement scale of the Communication and Influence strategy	
ITEM	**SOURCE**
Digital communications marketing	Cao *et al.* (2019); Benslama & Jallouli (2022)
Direct marketing	Yaa *et al.* (2011); Smith *et al.* (1997)
Sponsorship and events	Yaa *et al.* (2011); Smith *et al.* (1997); Benslama & Jallouli (2022)
Advertising strategy management	Filipe Lages *et al.* (2008); Slater & Olson (2001); Benslama & Jallouli (2022)
Brand image	Cao *et al.* (2019); Benslama & Jallouli (2022)
Promotion strategy	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Public relations	Filipe Lages *et al.* (2008); Slater & Olson (2001)
Sales force management	Filipe Lages *et al.* (2008)
Media allocation	Filipe Lages *et al.* (2008)

Measurement scale of the Product, Service and Brand strategy	
ITEM	**SOURCE**
Characteristics	Filipe Lages *et al.* (2008)
Brand name	Filipe Lages *et al.* (2008); Filipe Lages & Montgomery (2004)
Design	Filipe Lages *et al.* (2008)
Product/Service Quality	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Product labelling and packaging	Filipe Lages *et al.* (2008)
Brand reputation	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Brand awareness	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Brand loyalty	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Measurement scale of the Channel and Logistics strategy	
ITEM	**SOURCE**
Logistics and channel improvements	Chen *et al.* (2015)
Warehousing, inventory, stock optimization	Chen *et al.* (2015)
Channels and distribution network	Filipe Lages & Montgomery (2004)
Transport strategy	Filipe Lages & Montgomery (2004)
Budget for distribution	Filipe Lages & Montgomery (2004)
Measurement scale of the Pricing strategy	
ITEM	**SOURCE**
Wholesale price	Filipe Lages *et al.* (2008)
Retail price	Filipe Lages *et al.* (2008)
Pricing method	Filipe Lages & Montgomery (2004)
Profit margins	Filipe Lages *et al.* (2008)
Sales terms	Filipe Lages *et al.* (2008)
Customer credit	Filipe Lages *et al.* (2008)
Measurement scale of Effectiveness	
ITEM	**SOURCE**
I believe that we make good marketing strategies.	Visinescu *et al.* (2017)
The marketing strategies we make result in the desired outcomes.	
I am satisfied with the outcomes of our marketing strategies.	
Our marketing strategies improve organizational performance.	

Table A3. The internal consistency reliability and convergent validity indices

	Cronbach's alpha	Composite reliability Rho (A)	Composite reliability	AVE
GD	0.798	0.811	0.805	0.580
SD	0.817	0.827	0.821	0.605
EFF	0.921	0.939	0.922	0.750
METH	0.855	0.860	0.851	0.537
GPL	0.758	0.786	0.768	0.626
PPL	0.649	0.649	0.709	0.580
SPL	0.922	0.929	0.922	0.749
CIS	0.935	0.942	0.932	0.610
CLS	0.898	0.904	0.894	0.632
TPS	0.956	0.958	0.956	0.611
PS	0.922	0.924	0.922	0.665
PSBS	0.923	0.928	0.922	0.600

Bitcoin is an Environmental Disaster. Is the Indictment Distorted?

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Abstract: The literature is inundated with the claim that Bitcoin pollutes the environment. While the assertion is irrefutable, the unsettled issue is whether the indictment of environmental *disaster* is disproportionate or distorted. This is an empirical question; this paper evaluates it via two econometric methods. First, accepting carbon dioxide (CO_2) emission as a proxy for environmental pollution, the paper quantifies the elasticity of CO_2 emission in relation to electricity consumption in Bitcoin production. The results reveal that, while Bitcoin production based on conventional electricity is inelastic, carbon emission responsiveness to fossil fuel is significant. A 1% increase in Bitcoin's usage of coal-generated electricity leads to a 1.64% surge in CO_2 emission. Second, the study applies the error correction model to show that some electricity consumption shocks emanate from global coal prices driven by economic factors beyond Bitcoin's control. This raises the question of whether Bitcoin should shoulder the entire blame for the 1.64% pollution responsiveness. Therefore, the study makes two important contributions. First, Bitcoin's pollution impact varies according to timespan and electricity source. Second, the intensity of carbon emission from electricity consumption is aggravated by external market factors beyond Bitcoin's control. The findings should inform policymakers and enlighten environmental advocates.

Keywords: Bitcoin, Cryptocurrency, Elasticity, Greenhouse gas emissions, CO_2 emissions

Introduction

Some environment researchers ([Chamanara *et al.*, 2023](); [Wang *et al.*, 2022]()) have declared Bitcoin an environmental disaster. The pollution concerns are legitimate, but the denigrating adjectives are not incontrovertible. Indeed, it is questionable whether the indictment is distorted, and empirical research to give a balanced assessment is lacking, which is the value-add of the current paper. The problem of Bitcoin's environmental pollution is linked to its transaction validation method. The advantage of physical money or fiat currency (like the

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Australian Dollar) is that, once a person handles it, there is a guarantee that no one is spending it simultaneously somewhere, which may invalidate the transaction or raise annoying fraud suspicions to authorities. This is known as a *double-spending* problem in the cryptocurrency market. Consequently, there have been many unsuccessful attempts at digital currency in the past, like eCash, eGold, Hashcash, Bmoney, and Bit-Gold (Subramanian & Chino, 2015). The main dilemma confronting digital network pioneers is ensuring zero double-spending risk in digital currency without introducing a middle-trusted authority, like in the case of fiat money.

In 2009, Bitcoin was birthed, the first success in the current cryptocurrency generation, and overcame the double-spending problem by introducing what is called a *proof of work* (PoW) validation procedure (a computer-based consensus algorithm), using cryptography and blockchain (public ledger) technologies. The Bitcoin payment validation process using the PoW method involves an army of decentralised computers (called nodes) operated by public individuals or pools (known as miners) competing to solve a complex computer algorithm (or mathematical puzzle) to arrive at a consensus of whether the transaction is valid (no double-spending risk), qualifying the winning solver (or mining participant) to chain (or enjoin) the new block to the public ledger system. This is why the clever database is called Blockchain.

Bitcoin miners are incentivised with a reward of minted Bitcoin units and transaction fees. During the mining process, each node (participant's computer) must go through many rounds of guessing (called hashing) to solve a mathematical puzzle designed to validate Bitcoin transactions or generate a new Bitcoin unit. The first miner to achieve the correct solution receives the reward, and it becomes game over for the rest. The process continues for all subsequent production cycles. The hashing activity is highly competitive and demands intensive electricity consumption. Another Bitcoin construct that exacerbates electricity usage is that the Bitcoin money system has a built-in control to prevent excessive production of Bitcoin units from flooding the market speedily. This is achieved by adjusting the solution complexity (called difficulty). The mining difficulty is re-scaled after every 2016 blocks, approximately every two weeks. Excessive usage of electricity, coupled with the fact that Bitcoin predominantly uses fossil fuel (energy generated from natural gas, oil or coal), results in significant CO_2 emission potentials. This is classified as human-induced climate change.

Pollution-induced climate change is a critical societal concern due to its potential negative impact on the current economy and future generations. The consequential extreme weather conditions, among others, may disrupt the economy's productive resources and wellbeing. The problem of climate change is intricately linked to increasing CO_2 emissions from industrial production, including cryptocurrency mining. Historically, the issue of environmental preservation has been a contested terrain. For instance, "drops in emissions often provoke claims from climate sceptics that worries over global warming are exaggerated, while increases

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in emissions lead to concerns among environmental groups that not enough is being done to address the issue" (Cohen *et al.*, 2018, p. 58).

Nevertheless, financial market participants have increasingly befriended sustainable finance over the years. Evidence of the global shift towards sustainable finance is now common knowledge for academics and practitioners. An international auditing and consultancy firm, Price Waterhouse Coopers (PWC), conducts a periodic global survey of institutional investors with combined assets under management (AuM) of USD 50 trillion. In their latest report, PWC observes that there is "an unprecedented acceleration in the move towards environmental, social and fund governance-orientated (ESG-orientated) investments" (PWC, 2022, p. 2). They also perceive that "ESG-orientated funds are set to grow much faster than the market as a whole" (PWC, 2022, p. 7). For instance, the same report projects that ESG-oriented AuM should achieve USD 34 trillion by 2026 from USD 18 trillion in 2021.

In contrast, the cryptocurrency market continues to suffer escalating criticisms for lagging on eco-friendly investing. Bitcoin, as a firstborn and dominant cryptocurrency, shoulders much reproach with labels like "environmental disaster" (Wang *et al.*, 2022, p. 384). The accusations arise because Bitcoin mining (or production) consumes excessive electricity, often sourced from fossil fuel, a significant contributor to greenhouse gas (GHG) emissions. GHG emissions raise a socio-economic problem because they trap (or house) heat in the atmosphere and then emit it back to the earth with detrimental consequences. This heat-trapping mechanism of GHG is known as the greenhouse effect. The greenhouse effect is part of a more concerning problem with its causal relationship with global warming or climate change. The prominent members of GHG are sulfuric hexafluoride (SF_6), nitrogen dioxide (N_2O), methane (CH_4), and carbon dioxide (CO2). The scope of the current study is confined to the latter because it is known to be the more problematic of the four gases.

The rest of this paper has the following sections: the Bitcoin market; a literature review; the study methodology; empirical results; discussion of results; and a conclusion.

Background

The first transaction of Bitcoin occurred on 12 January 2009, but its actual activity took off from a minuscule price of $0.09 in July 2010. Since then, Bitcoin has experienced volatile fluctuations characterised by several rallies, crashes, and an all-time high price of over USD 69,000 in November 2021, and then oscillating to the current price (January 2024) of just over USD 40,000. The cryptocurrency industry is currently valued at USD 1.85 trillion, and Bitcoin's capitalisation of more than USD 900 billion, a dominant market share of just under 50%. Bitcoin's global legal status varies from an absolute ban (Bahrain, Burundi, Cameroon, Gabon, Georgia, Guyana, Kuwait, Lesotho), or an implicit ban (Algeria, Bangladesh, China,

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Egypt, Iraq, Morocco, Nepal, Qatar, Tunisia, Libya, Macao, Maldives, Vietnam, Zimbabwe), to full adoption as a legal tender in El Salvador on 5 June 2021 and Central African Republic on 28 April 2022 (Kshetri, 2022; US Congress Library, 2022). The value of Bitcoin as a type of technological progress is now well-known. Bitcoin has tested blockchain technology, which has promising potential in education and commercial applications like smart contracts, decentralised notaries, digital identity, digital academic certificates, and central bank digital currency, *inter alia* (Gopane, 2019; 2023).

Previous studies into the problem of Bitcoin and cryptocurrency environmental pollution were predominantly in the research fields of mathematics, engineering, and natural sciences, and less in financial economics (Wang *et al.*, 2022). Natural science research approaches often help with scientific quantifying or tracing GHG footprints. However, the resultant absolute measures should benefit from further econometric analysis. The current paper applies econometric modelling to investigate the elasticity of environmental degradation (proxied by CO2) with respect to electricity usage of Bitcoin mining. This investigation is essential for several reasons. First, it is important not only to understand the change (absolute magnitude) in determinants of CO2 but also its correlation, all within the same number. Economists call such a measure elasticity (for related applications, see, Cribari-Neto, 1996). Second, the recent turbulent events, like the collapse of the cryptocurrency exchange, FTX, criticisms of Bitcoin's pollution status by influential entrepreneurs (Martin & Nauman, 2021), and US political rhetoric (Ferré-Sadurní & Ashford, 2022) regarding permits for fossil fuel operated crypto mines, tend to hype questionable environmental anxieties.

Literature Review

Whereas environmental economics has a long history of evaluating pollution emanating from industrial production or economic growth (Nordhaus, 1977; 1991; 1992), financial markets are recently revitalised through the ESG debate (Matos, 2020; Pástor *et al.*, 2021). Interestingly, the rate of preference shift towards sustainable investment seems to correlate with research deepening in the subthemes of climate finance (Giglio *et al.*, 2021), green finance (Malhotra & Thakur, 2020), green mutual funds (Chang *et al.*, 2012); green bonds (Zerbib, 2019), and green cryptocurrency (Oğhan, 2022). The latter is the least green asset, especially Bitcoin, which is the subject of the present study. The research that interrogates Bitcoin's environmental impact (Wendl *et al.*, 2023) straddles the literature streams that examine the Bitcoin network, blockchain (Gopane, 2019) electronic or e-waste (de Vries, 2019; de Vries & Stoll, 2021), and Bitcoin electricity consumption measurement (Küfeoğlu & Özkuran, 2019). The current study proceeds to use electricity data generated and refined by other researchers (Cambridge Centre for Alternative Finance, 2023).

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Past research (see review by Wendl *et al.*, 2023) concurs that Bitcoin, due to its hashing brute-force and PoW consensus algorithm, is an electricity-intensive operation with significant pollution burdens, but there is a disagreement on the scope of the problem. One set of researchers (for example, Goodkind *et al.*, 2020; Mora *et al.*, 2018; O'Dwyer & Malone, 2014) appear to align with the media screams that "Bitcoin ...is a dirty currency" (Martin & Nauman, 2021, p. 21) alluding to that its carbon footprint is excessive, and an environmental crisis. Another stream of literature (Koomey, 2019; Krause & Tolaymat, 2018; Masanet *et al.*, 2019) that happens to side with the sentiment of the Bitcoin proponents is that Bitcoin's pollution estimates are prone to mistakes and erroneous assumptions, and are often misleadingly overstated. The disagreement centres mainly on how Bitcoin electricity consumption is computed to quantify the resultant GHG emissions. The exact quantity of Bitcoin's electricity usage by its miners is unknown. Therefore, researchers approximate this information through a combination of operational assumptions and estimates of profitability variables, including hash rate, miners' rewards, difficulty changes, equipment efficiency, and others (comprehensively detailed in Koomey *et al.*, 2019).

An illustration of the flagged debate is exemplified in Mora *et al.*'s (2018, p. 931) staggering projection that "Bitcoin ... could alone produce enough CO_2 emissions to push global warming above 2°C within less than three decades". After a comprehensive rebuttal, Masanet et al. (2019, p. 654) argue that the *2°C global warning* threat is "fundamentally flawed and should not be taken seriously by the public, researchers or policymakers". Based on observation of the literature, it is evident that a balanced and objective research agenda is necessary.

Methodology

The empirical design starts from the literature consensus that Bitcoin's production methods lead to significant pollution. However, the current study raises the question of whether the elevation of Bitcoin pollution status to *environmental disaster* is a distorted indictment. Methodologically, the current study applies two econometric modelling procedures: elasticity analysis based on short-run and long-run decomposed time series; as well as a vector error correction model (VECM). The investigation will be aligned with the following empirical hypotheses.

First hypothesis [H1]: *CO_2 emission responsiveness to electricity consumption varies according to short-term energy usage in Bitcoin production*. The rationale for this hypothesis is that, if the short-run responsiveness differs from the long-run, then the solution for Bitcoin's pollution problem ought to be adjusted accordingly. A related curiosity is whether the label of Bitcoin's *environmental disaster* is valid or uniform throughout short and long-run time spans.

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Second hypothesis [H2]: *The relationship between CO2 emission and electricity consumption in the Bitcoin market is compounded by external factors.* The thinking behind this hypothesis is that, if shocks outside Bitcoin's operation significantly help the pollution problem of CO2, then it will help policymakers consider appropriately attributed intervention methods like tax incentives. Another way to look at it is whether it is distortionary to level the entire problem at Bitcoin production in the presence of significant external shocks.

Figure 1 presents a descriptive profile of key datasets for the study, namely Bitcoin's electricity consumption and CO2 emissions. While there is some interesting and visible co-movement in the graph, an examination of absolute numbers alone is not enough to provide answers to H1 and H2. So, econometric analysis will follow. Figure 1 shows some visible co-trending of the variables with CO2 lagging and overshooting Bitcoin during times of extreme shocks, consistent with economic intuition.

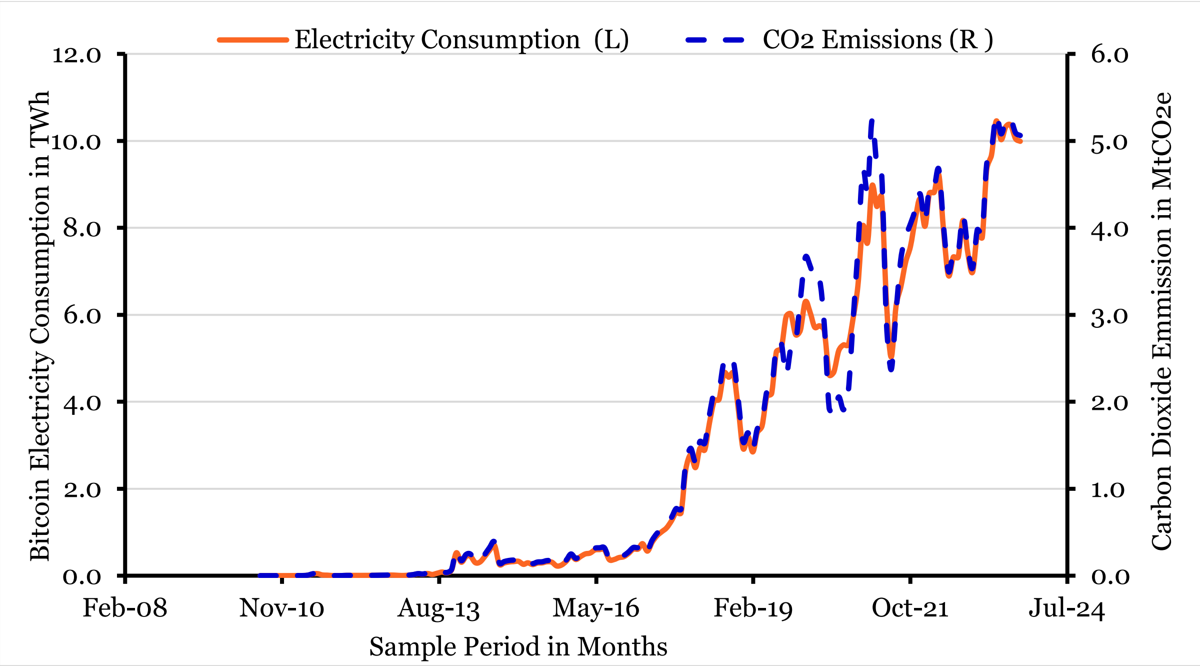


Figure 1. Plot of Bitcoin Electricity Consumption and Carbon Dioxide Emission. (Source: Author's graphics)

Model 1: Carbon Emissions Elasticity

This section implements the elasticity analytical framework for Bitcoin energy use and CO2 emission. The results will address the first study hypothesis, H1. The purpose of computing the elasticity of carbon emissions in response to Bitcoin electricity usage (E) is to provide the responsiveness of carbon emissions to changes in E; more specifically, a combined effect of absolute change and correlational intensity of E's usage. The study quantifies elasticity coefficients for the full data series, short-run and long-run co-movements of CO2 and E, adapting the modelling procedure of Cohen *et al.* (2018). The elasticity analysis will be based on Equations (1), (2), and (3), along with Table 1 for variable definitions.

$$HP\ Filter:\ \min_{\tau}\sum_{t=1}^{T}(s_t - s_t^{\tau}) + \lambda\sum_{t=1}^{T}[(s_t^{\tau} - s_{t-1}^{\tau}) - (s_{t-1}^{\tau} - s_{t-2}^{\tau})]^2 \quad (1)$$

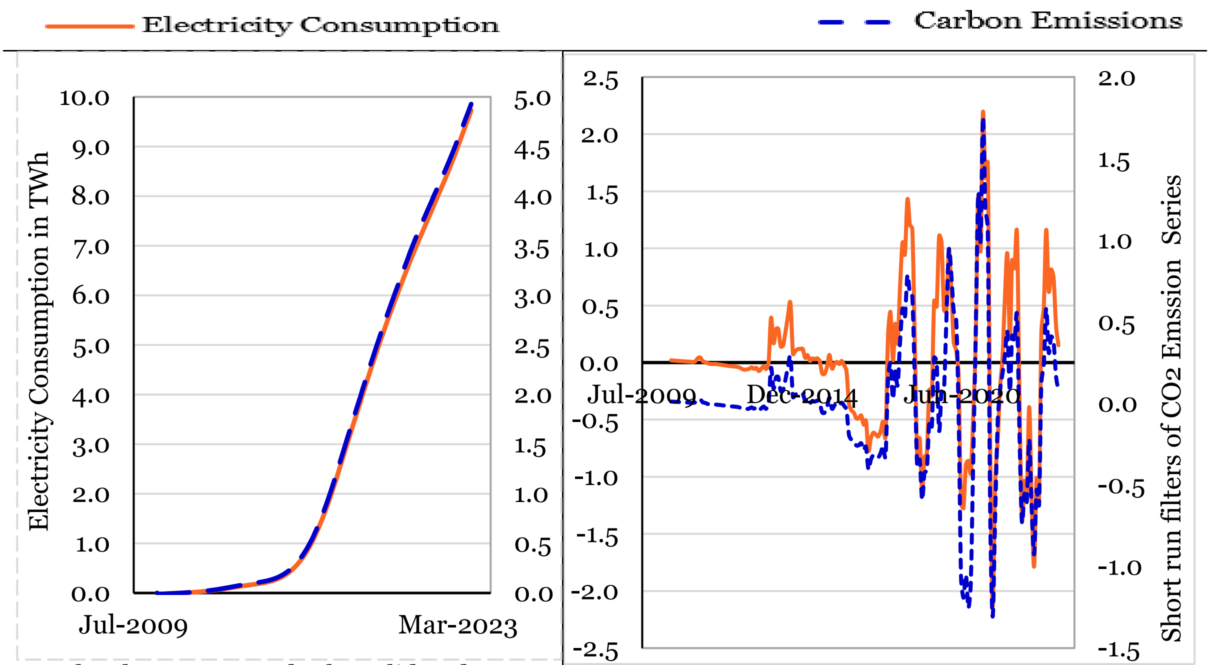
$$log\mathcal{C}_t = \mu + \eta log E_t + v_t \quad (2)$$

$$\eta = \frac{\Delta\log\ \mathcal{C}_t}{\Delta\log\ E_t} \quad (3)$$

Table 1. Variable Definitions

$s_t = \in (E_t, \mathcal{C}_t)$
E = Total electricity in different transformations, sequentially.
$\mathcal{C}$ = CO2 from coal energy in different transformations, sequentially.
t = 1,2,3,..., T, is an index of time in months
c = Cycle
τ =Trend
λ = Smoothing parameter, conventionally set at 14400 for monthly frequency.
η = Elasticity
μ = Intercept
v_t = Error term

Source: Author's compilation



Panel A: long-run trend. The solid and dashed lines represent long-run trends of Electricity Consumption and CO2 Emissions, respectively.

Panel B: Short-run cycle filters. The solid and dotted lines represent short-run cycles of Electricity Consumption and CO2 Emissions, respectively.

Figure 2. Bitcoin Electricity Consumption and Carbon Emissions Short Run Cycles. (Notes: Panels A and B are decomposed from Figure 1. In both graphs, the left vertical axes record Electricity units, while the right vertical axes capture CO2. Source: Author's graphics)

Equation (1) is the commonly used Hodrick-Prescott (HP) time series filter by Hodrick & Prescott (1997). The general purpose of the HP filter is to decompose a time series (say, s_t) into long-run trend (s_t^{τ}) and short-run cycle ($s_t - s_t^{\tau}$). In the current study, the data sets for electricity usage and CO2 emissions (plotted in Figure 1), are filtered into the short- and long-

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run series, which result in Figure 2, after decomposition. The decomposed series are used to estimate elasticity coefficients using ordinary least squares (OLS) regression. The OLS model is estimated in growth rate transformation to control for possible spurious behaviour. Equation (2) is replicated thrice, and elasticity is quantified per Equation (3) from each regression output.

Model 2: Vector Error Correction Model

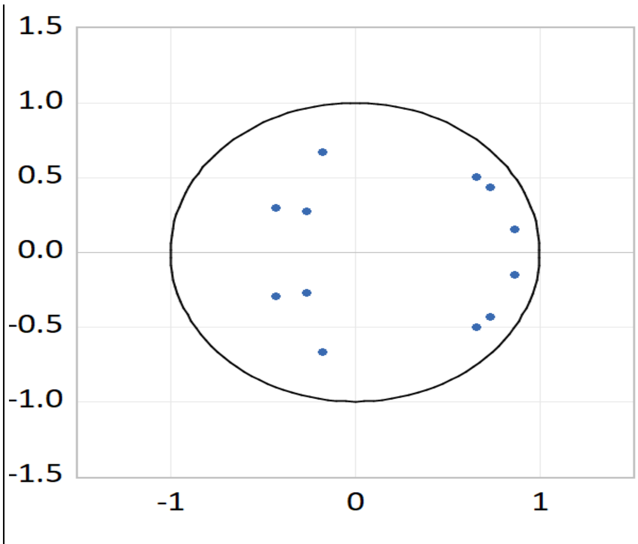
Model 2 implements a vector error correction model, VECM(p), which will be used to provide an answer for H2. This model will enable the generation of regression analysis based on the Granger-Causality test and Impulse Response Functions.

$$\Delta y_t = \alpha\beta' y_{t-p} + \sum_{\ell=1}^{p} \Phi_\ell \Delta y_{t-\ell} + \epsilon_t \tag{4}$$

The variable definitions in Equation (4) are as follows. The subscripts t and ℓ are time in months, and lag structure with order $p = 5$, respectively. The response variable, Δy_t ($= y_t - y_{t-1}$) is a vector of endogenous variables, Carbon emissions, electricity consumption, global coal price, and Bitcoin price. The parameters, α (measuring speed adjustment), β (cointegration parameter), and Φ (short-run coefficients) are estimated in the model and have dimensions of $k \times r$, for the first two, and $k \times k$ for the latter. The last variable is the error term, which is assumed to follow a normal distribution.

Model validation

Table 2. Model Validation: Roots of characteristic polynomial endogenous variables



Root		Modulus
0.8629	-0.1507i	0.8759
0.8629	+0.1507i	0.8759
0.7349	-0.435i	0.8540
0.7349	+0.435i	0.8540
0.6565	-0.5048i	0.8281
0.6565	+0.5048i	0.8281
-0.1753	-0.669i	0.6916
-0.1753	+0.669i	0.6916
-0.4292-	-0.2939i	0.5202
-0.4292	+0.2939i	0.5202
-0.2594	-0.2711i	0.3752
-0.2594	+0.2711i	0.3752

Notes: No root lies outside the unit circle, meaning the model satisfies the stability condition. **Source:** Author's computation

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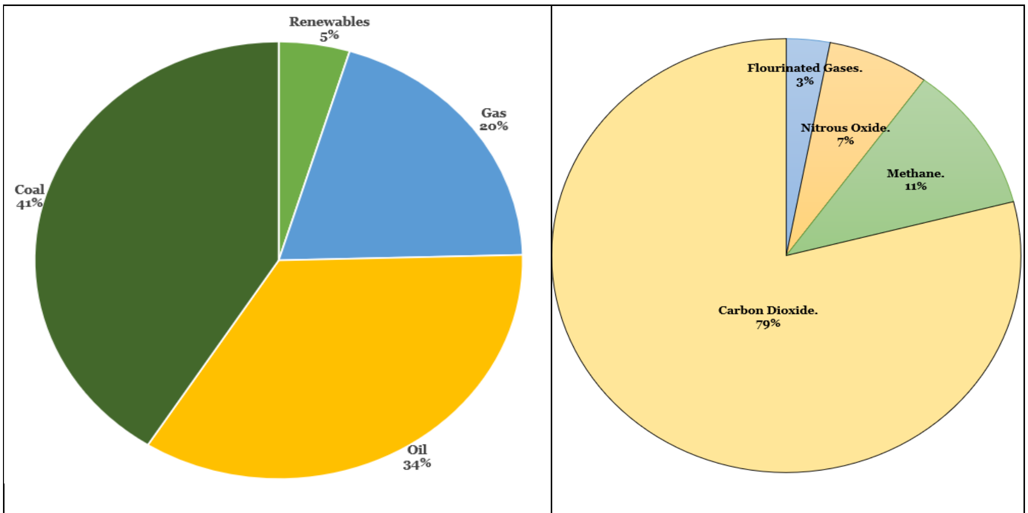
VECM requires that the endogenous variables have cointegration of degree one, that is I(1). Among other things, this means that the relevant time series must become stationary after first differencing, and the condition is satisfied in the current study. The econometric theory of VECM also requires that, before the model can be used, it must satisfy the stability condition. The current study passes, as per Table 2, which shows that all roots of characteristic polynomials lie within the unit circle, confirming model stability. Other tests like lag selection structure (resulting in an order of 5) and cointegration (resulting in a rank of 3) were tested with fully satisfactory results, but not reported due to space constraints. Bitcoin carbon emission has a long-run equilibrium relationship (cointegrated) with Bitcoin electricity consumption and global coal prices.

Data characteristics

This empirical study uses monthly data for the entire Bitcoin network from July 2010 to October 2023. The data on CO2 emissions and electricity consumption are sourced from the Cambridge Centre for Alternative Finance (2023). CO2 is expressed in million tonnes of carbon dioxide equivalent, abbreviated MtCO2e. This means that CO2 emissions are standardised on their equivalent of 100-year global warming potential (GWP100). Electricity consumption is measured in terawatt hours (TWh). Further details of data gathering assumptions are explained by the data source, Cambridge University. Figure 3 (Panel A) shows that sources of electricity in the Bitcoin industry are renewable energy (nuclear, wind, hydro, and solar) as well as fossil fuels (natural gas, oil, and coal). Looking at Panel A, it is evident that fossil fuels are the primary sources of electricity for Bitcoin production. Figure 3 (Panel B) shows the relative sizes of the leading GHG, namely, fluorinated gases (3%), nitrous oxide (7%), and methane (11%), while CO2 has a dominant share of 79%.



Panel A: Bitcoin's energy use by source	**Panel B:** Types of GHG emissions

Figure 3. Life cycle greenhouse gas (GHG) emissions. (Notes: Panel A shows that coal is a dominant energy source, and Panel B says CO2 has the highest GHG emissions. Source: Author's graphics)

Additional data sources are used for the purpose of running the VECM regression. Monthly dataset of Bitcoin prices in USD is obtained from the Coin Metrics website (2023), and the dataset for global coal prices in USD is obtained from the International Monetary Fund (2023). The two datasets are plotted in Figure 4, and the graphs show a visible co-movement.

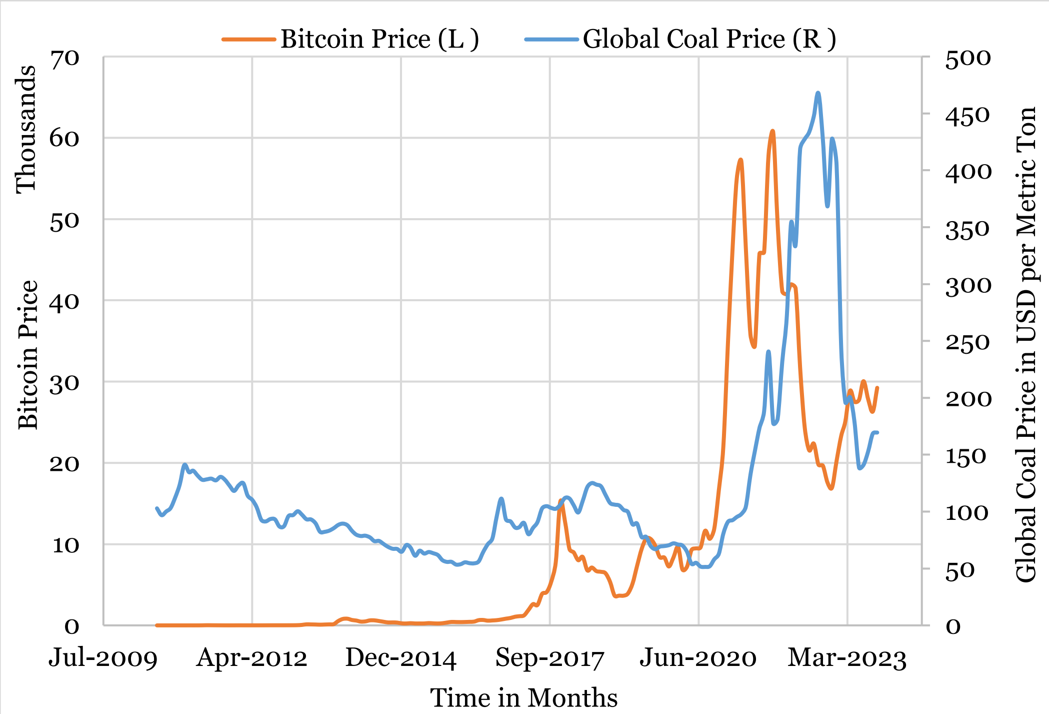


Figure 4. Plot of Bitcoin Price and Global Coal Price (Source: Author's graphics)

Empirical Results

Carbon emission elasticity

Table 3 presents the results of carbon emission elasticity coefficients with respect to Bitcoin's coal-generated electricity consumption. Panel A of Table 3 shows that the responsiveness of coal-based CO2 emission to electricity varies according to short-run (1.03%), long-run (1.26%), and unsegregated sample (1.64%). Based on the economic definition, if the elasticity coefficient is less than one, it is considered inelastic; if it is equal to one or more, it is elastic. In the current case, the results show that coal CO2 emissions are always elastic with respect to electricity usage. More specifically, the results reveal that, when elasticity increases by one unit in the short run, CO2 emissions increase more. In the long run, the increase is one-for-one, which supports the intuition of long-run equilibrium, as depicted in Figure 2, Panel A. An important observation to note in Panel B of Table 3 is that the responsiveness of aggregate CO2 emissions with respect to total electricity consumption in Bitcoin operations is inelastic both in the short and long runs. Table 3 shows that there is value in disaggregating the datasets into short- and long-run time horizons. Given the results of elasticity analysis, we fail to reject

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H1 and find a significant variance in short and long-run CO2 emissions' responsiveness with respect to electricity consumption.

Table 3. Elasticity – Responsiveness of CO2 Emission to Electricity Usage (Source: Author's computation)

Details	Transformation	Elasticity	Std Error	P-value
Panel A: CO2 (from **coal**) elasticity with respect to total electricity consumption				
Long run	HP Filter	1.03	0.0859	0.0000***
Short run	HP Filter	1.26	0.0304	0.0000***
Full Series	Before HP Filter	1.64	0.0897	0.0000***
Panel B: CO2 elasticity with respect to total electricity consumption				
Long run	HP Filter	0.73	0.0100	0.0000***
Short run	HP Filter	0.12	0.0120	0.0000***
Series	Before HP Filter	0.28	0.0184	0.0000***

Legend: Statistical significance level *** 1%. HP Filter means Hodrick-Prescott time series filter by Hodrick & Prescott (1997)

Results of Vector Error Correction Model

Table 4. Granger Causality Test from Vector Error Correction Model (VECM). (Source: Author's computation)

Variables	Wald Test (χ^2)	Degrees of freedom	P-value
Panel A -Response: CO2 Emission			
Electricity Consumption	*127.6058*	*5*	*0.0000****
Global Coal Price	*50.8214*	*5*	*0.0000****
Bitcoin Price	*69.3251*	*5*	*0.0000****
Panel B - Response: Electric Usage	0.0000		0.0000***
Global Coal Price	44.0776	5	0.0000***
Bitcoin Price	54.3591	5	0.0000***
Panel C: Response: Bitcoin Price	0.0000		0.0000***
Electricity Consumption	42.7617	5	0.0000***
Global Coal Price	12.4016	5	0.0297**

Legend: *** 1%, **5%

The results of VECM are presented in the form of impulse response functions or IRF (in Figure 5) and Granger-causality test (in Table 4). The intuition of Granger causality is not the same as the English notion of cause-and-effect relationship but is a statistical concept that means one variable (specifically, time series) helps to predict another (Granger, 1969). In this regard, using the verb, *cause,* on its own may be imprecise or misconstrued. Panel A of Table 4 shows that electricity consumption, global coal price, and Bitcoin price individually and collectively cause Granger-caused CO2 emissions. To clarify further, Granger causality reveals that, with the global coal price included in the model, the predictions of Bitcoin CO2 emissions are improved and more accurate. The reverse is also true: excluding global coal prices will lead to an understatement of the predictions of Bitcoin CO2 emissions. This implies that, while it is

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essential to include global coal prices for accurate Bitcoin CO2 emissions, it is equally vital to acknowledge that Bitcoin's environmental pollution is linked to other factors beyond Bitcoin's control. This result is strengthened by the presence of an indirect effect (second transmission channel) of the global coal price on carbon emissions. That is the global coal price Granger-caused electricity consumption (Panel B) and Bitcoin price (Panel C), respectively.

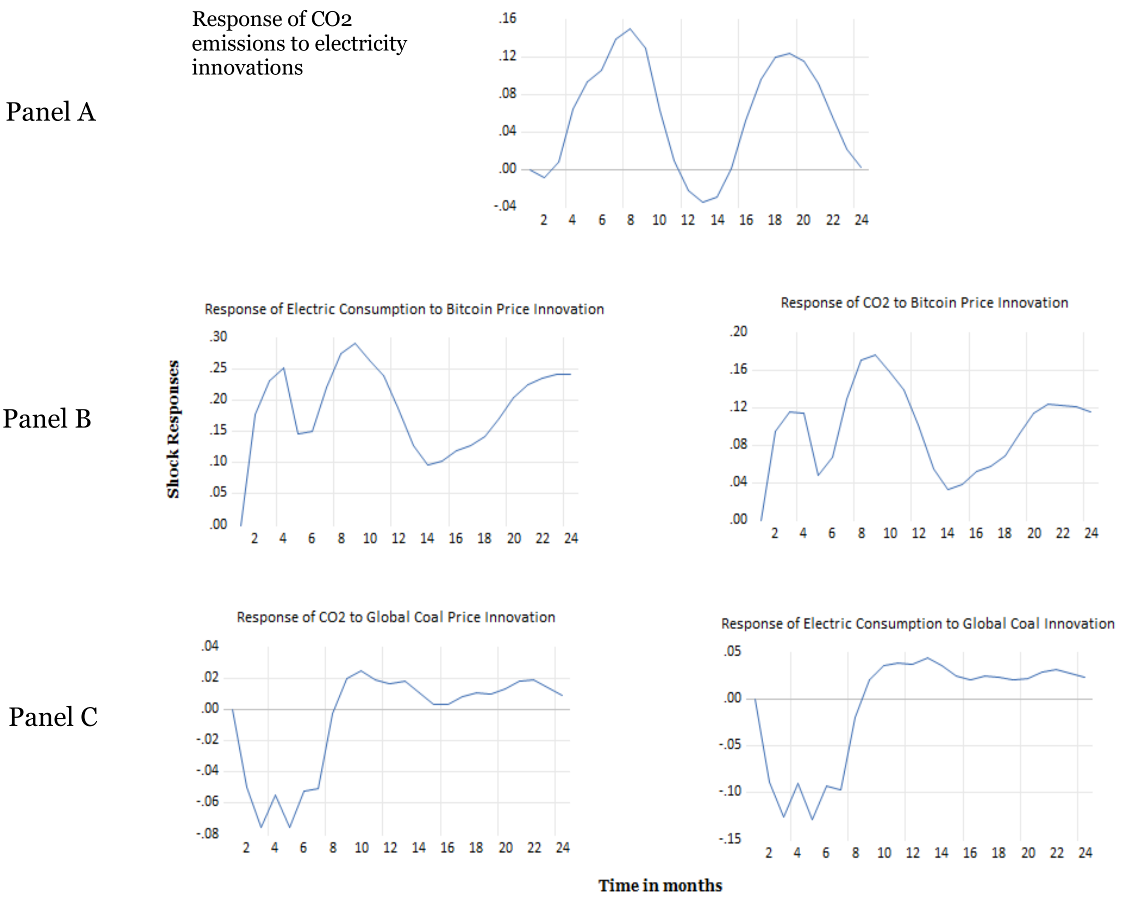

Figure 5. Impulse Response functions using Cholesky One Standard Deviation Innovations, adjusted for degrees of freedom (Source: Authors' graphics)

The IRF results of Figure 5 complement the findings of Table 4. Based on econometrics theory, IRF traces one standard deviation shock on one endogenous variable and its impact on another variable, keeping other variables within the VECM system unchanged. In each of the five graphs of Figure 5, the vertical axis measures the responses (in percentage) of Carbon emissions to one standard deviation from another variable (say, electricity consumption). The horizontal axis represents the time in months that have passed since the transmission of a shock.

Panel A of Figure 5 says that one standard deviation shock in Bitcoin electricity consumption leads to a steep increase in Carbon emissions, reaching 0.15% before turning into a cyclical response pattern within a band of -0.4% and 0.16, with more elevated positive peaks than negatives. Panel B shows that after one month, shock transmissions from Bitcoin price to CO2

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emissions respond with a gradual increase after one month, making the first peak at 0.12% in the fourth month, before turning into a cyclical pattern in the range of 0.4% to 0.16%, then tapes-off after two years (24 months). Panel C shows that a one standard deviation shock in global coal price leads to an immediate decrease in CO2 emissions and remains low within a cyclical band of -0.6% and -0.8%. Then, it gradually overshoots to 0.2% after eight months before dissipating four months later. Judging by the similarity in shock patterns of Panel B (elasticity usage and Bitcoin price) and Panel C (electricity usage and global coal price), this may indicate the intensity of indirect shocks these variables convey to CO2 emissions. The results of IRF corroborate the Granger-causality tests in that not only are CO2 emissions responsive to direct shocks from global coal price, but the same global coal price impacts electricity usage and Bitcoin price. This means that there is another indirect shock transmission to CO2 emissions from global coal prices. Given the aforesaid, and based on the VECM results in general, we fail to reject H2, resulting in the finding that CO2 emissions have a necessary linkage with external economic factors (outside Bitcoin's operations) and global coal prices. This nexus is both statistically and economically significant.

Discussion of Results

There is an emerging body of literature characterised by a common view that Bitcoin is an *environmental disaster*. Such studies often prompt hyped warnings like "Bitcoin is an absolute energy and *environmental disaster*" (Wang *et al*., 2022, p. 384, emphasis added) or "the environmental footprint of Bitcoin mining across the globe: *call for urgent action"* (Chamanara *et al*., 2023, p. 1, emphasis added), to mention a few. The current study examines whether the indictment is distorted or there is inadvertent imprecision.

First, the results of elasticity analysis show that general CO2 emissions with respect to total electricity consumption (regardless of source, renewable or fossil fuel) are inelastic. In contrast, Bitcoin's fossil fuel-based CO2 emissions are elastic, one to one in the long run and 1.64 in the short run. The variance in short- and long-runs of CO2 responsiveness implies that policy interventions on Bitcoin's CO2 emissions may need to differ for short-run and long-run time horizons, if deemed necessary. Similarly, it is probably imprecise to declare Bitcoin equally disastrous for both short- and long-run impacts.

Second, according to VECM findings, Bitcoin's CO2 emissions are cointegrated with both electricity consumption and global coal prices. Also, based on Granger causality evidence, accounting for global coal prices is necessary to arrive at more accurate predictions of Bitcoin's CO2 emissions. Additionally, the global coal price has a significant indirect effect on Bitcoin's CO2 emissions via Bitcoin electricity consumption and Bitcoin price. The implication is that, by quantifying the predictions of Bitcoin's carbon emissions without accounting for necessary external market factors like global coal price, then such magnitudes of environmental pollution will be understated. The logical conclusion of this point is that, if the inclusion of external economic factors is statistically and economically significant, then Bitcoin's pollution indictment ought to be equally shared with co-sources of pollution. To recapitulate, studies calling for drastic policy intervention like the Bitcoin pollution tax (Chamanara *et al.*, 2023) should re-think whether Bitcoin will be a precise tax incidence without carefully considering short- and long-run carbon emissions and, more importantly, external drivers.

Conclusion

This study has used two analytical methods to inquire whether there is imprecision in labelling Bitcoin as a standalone *environmental disaster*. Such research conclusions are corroborated by studies demanding urgent tax discipline on Bitcoin, which appear to be an imprecise indictment and probably a hasty policy call. Using Hodrick-Prescott filtering and elasticity analysis, the results show that the CO_2 emission reactions from fossil fuel Bitcoin productions differ according to short- and long-term responsiveness. In contrast, non-fossil fuel production shows inelastic CO_2 emissions. The evidence based on *the vector error correction* model shows that it is necessary to include external factors, such as global coal prices, for accurate predictions of Bitcoin CO_2 emissions.

The moral of the story is that GHG emissions contribute to climate change, which has "the potential to impact the health and well-being of nearly every person on the planet" (Giglio *et al.*, 2021, p. 16). While Bitcoin's production technology of using a proof-of-work consensus algorithm leads to intensive electricity consumption, the study shows that excessive electricity usage on its own is not problematic, but the source of electricity matters, like fossil fuel usage, particularly coal energy.

The practical implication of the study is that policy interventions need not only to consider short- and long-run variations in CO_2 emissions but also to be aware of the aggravation of pollution impact arising from external economic factors (outside Bitcoin's control) that impact Bitcoin production. Accordingly, Bitcoin's environmental indictment should be balanced according to the time horizon of carbon emissions and inseparable co-polluting sources. Regarding study limitations, while Bitcoin is a dominant cryptocurrency, including all cryptocurrencies in a study like this would be an improvement. Further study is recommended to generalise a similar analysis on the entire cryptocurrency market, especially those crypto operations that use fossil fuel in their productions.

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A Novel AutoCNN Model for Stock Market Index Prediction

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Abstract: Stock markets have a significant impact on the economic growth of countries. Predicting stock market indices has been a complex task in recent years. Indeed, many researchers and financial analysts are keenly interested in the research area of stock market prediction. In this paper, we propose a novel framework, titled AutoCNN, based on artificial intelligence techniques, to predict future stock market indices. AutoCNN is composed mainly of three stages: (1) A Convolutional Neural Network (CNN) for Automatic Feature Extraction; (2) The Halving Grid Search algorithm combined with a second CNN model for prediction of stock indices; and (3) Evaluation and recommendation. To validate our AutoCNN, we conduct experiments on two financial datasets that are extracted in the period between 2018 and 2023, which includes several events, such as economic, health and geopolitical international crises. The performance of the AutoCNN model is quantified using various metrics. It is benchmarked against different models and it proves to have strong prediction abilities. AutoCNN contributes to emerging technologies and innovation in the financial sector by automating decision-making, leveraging advanced pattern recognition, and enhancing the overall decision support system for investors in the digital economy.

Keywords: Stock index prediction, automated deep learning, crisis periods, financial decision-making, digitalised economy

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Introduction

The financial sector plays an important role in the growth of economics of countries. A financial market is a physical or virtual place where market participants (buyers, sellers) meet to negotiate financial products (Grieger, 2003). Various economists and researchers have proven that there exists a link between financial development and economic growth (Agbloyor *et al.*, 2014). Stock markets, which are a particular type of financial market, are complicated financial businesses (Abraham *et al.*, 2001). There are various factors that affect the stock market indicators on a given day, such as industry performance, political changes, and economic variations (Goonatilake & Herath, 2007). Due to these factors, stock prices become highly unpredictable (Fathali *et al.*, 2022) and prediction is a challenging task.

In the literature, the stock price prediction approaches can be categorized into three types: (1) fundamental analysis; (2) technical analysis (Lawrence, 1997); and (3) machine learning models (Murkute & Sarode, 2015). The fundamental analysis considers economic factors as fundamentals and it is mostly employed for long-term predictions (Zouaghia *et al.*, 2023). The technical analysis is mainly based on charts that are able to identify trends and patterns in stock prices. However, the machine learning (ML) approach is based on artificial intelligence (AI) techniques for predicting stock market prices after building, training, and testing such a model. The process of stock index prediction can be seen as the prediction of future price variations by learning and analysing the historical stock data. Moreover, researchers (such as Kompella *et al.* 2019) demonstrated that traditional models did not generate an acceptable level of accuracy in the stock market prediction task and showed that models based on artificial intelligence techniques are more accurate.

In recent years, digital transformation has affected innovation in the majority of sectors of the economies of countries (Mgadmi *et al.*, 2021). Various researchers have demonstrated the impact of digital transformation on enhancing innovation in business (such as Li *et al.*, 2023) and implementing preventive tax risk management measures (Strauss *et al.*, 2020). Thus, the use of the Internet gives rise to digitization in the economy and it enhances the productivity of existing activities (Carlsson, 2004). Furthermore, the integration of artificial intelligence into economic activities represents a digitalization within the economic sector (Glushchenko *et al.*, 2020). In particular, the application of technologies in financial sectors, such as financial services, banks, companies and especially the financial markets, have recently given rise to the Financial Technology (Fintech) sphere (Abbasov *et al.*, 2020); it enhances economic growth (Chen *et al.*, 2022). As a result, the utilization of information with technologies has significantly facilitated the development of market economy strategies. Furthermore, digital

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technologies have also spurred business transformations across the value chains of all sectors.(Mukherjee *et al.*, 2023).

Recently, the use of advanced artificial intelligence techniques for business and, especially, to resolve financial problems have assisted us to have a global vision of future financial investments. Machine learning, which is a subfield of artificial intelligence, is one such tool that helps investors to make future stock market predictions (Leung *et al.*, 2014; Liu *et al.*, 2022; Mukherjee *et al.*, 2023). Deep learning is a subset of the machine learning technique, and most deep learning methods employ neural network architectures (Shinde & Shah, 2018). One of the most commonly practiced uses of neural networks are data prediction models, such as the forecasting of stock market prices based on stock historical data (Srivinay *et al.*, 2022). Neural networks are considered one of the common emerging generation of deep learning methods that demonstrate great abilities in solving complex problems (Aghapour *et al.*, 2023). Examples of neural-network models that are applied in stock market prediction are: Convolutional Neural Networks (CNNs); and Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) (Song & Choi, 2023), and Simple Recurrent Neural Network (SRNN) (Dey *et al.*, 2021). For this reason, we have chosen to apply a neural network-based model in our research work to enhance prediction in the stock market field. Investors need a more performant model to provide predictions to invest prudently during periods of uncertainty caused by many factors.

The originality of our contribution lies in:

1. CNN is applied in two different stages (the first step is in the task of automatic features extraction from financial stock data; the second step is in the task of stock index prediction). CNN is widely applied to extract features from charts (spatial dimension), but here we enhance its application to extract features from time series data (temporal dimension). It automates the process of features extraction. Additionally, CNN shows strong abilities in the task of prediction.
2. The Halving Grid Search (HGS) algorithm, which is rarely used in the literature, is hybridized with CNN to optimize its hyperparameters automatically. This combination of algorithms (CNN-HGS-CNN) was not applied previously in the task of stock index prediction.
3. The Automated Deep Learning model (AutoDL) is a recent artificial intelligence technique and has not been applied in the task of stock price prediction. A few papers in other fields (such as computer vision, natural language processing, speech recognition, and healthcare) use AutoDL and the results are prominent (Liu *et al.*, 2020; Faes *et al.*, 2019). Besides that, some authors automated a part of models and not all the process (Yi *et al.*, 2020).
4. AutoCNN can be considered as a valuable tool, because successful stock market prediction also requires an understanding of financial market behaviour. AutoCNN is trained on stock data that contains different crisis periods; thus it enhances the prediction during high volatility.

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5. The application of AutoCNN in predicting stock markets contributes to ongoing research in the intersection of finance and artificial intelligence. This research contributes to the development of novel combinations of hybrid models and insights, fostering innovation and knowledge advancement in both fields.

The rest of this paper is structured as follows. The following section describes a synopsis of related studies. The subsequent section details the proposed approach by analysing the data used and the steps applied to perform the task of stock index prediction. Section 4 details the conducted experiments and discusses the achieved results. Section 5 talks about limitations of the proposed approach. Section 6 presents the conclusion and proposes future directions. The final section has three appendices.

Related Literature

In the literature, various machine and deep learning models were suggested to predict future stock price indices of stock markets. Generally, two types of deep learning neural networks are used, namely CNNs and RNNs. These two networks have lately shown strong abilities in the task of stock index prediction (Zouaghia *et al.*, 2023).

The SRNN algorithm was proposed by Elman (1998); hence, it is called an *Elman Network*. It has shown strong abilities in identifying sequential data insights and predicting stock prices. The LSTM model is one of the most successful RNN architectures (Fathali *et al.*, 2022) and it is widely applied in the task of prediction of sequential data. The memory mechanism in LSTMs plays a crucial role in their ability to handle sequential data tasks such as time series prediction (Ozbayoglu *et al.*, 2020). The GRU model is a variant of RNN that was proposed in 2014 (Samarawickrama & Fernando, 2017). It excels in sequential data modelling, particularly in scenarios where fast training, computational efficiency, and effective handling of short-term dependencies are priorities.

Samarawickrama & Fernando (2017) proposed a RNN approach for predicting daily stock prices of some selected listed companies of the Colombo Stock Exchange (CSE). Experiments were conducted on three models: SRNN, GRU and LSTM networks. The authors chose as input three variables (Low, High, and Close prices).

Hoseinzade & Haratizadeh (2019) proposed a CNN-based framework that applied the CNN to gather data from a variety of sources from different stock markets, such as S&P500, NASDAQ, DJI, NYSE, and RUSSELL indices. After that, the model was applied to predict the next day's direction of movement for the considered indices. The authors tested two principal configurations of the CNN model: 2D-CNN and 3D-CNN. Their models were evaluated using the F-measure metric.

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Gao *et al.* (2021) applied an optimized GRU and LSTM models based on the use of various technical indicators with financial data. These two models were merged with two other methods, LASSO and Principal Component Analysis (PCA), to optimize their hyperparameters.

Fathali, Kodia & Ben Said (2022) applied the RNN, LSTM, and CNN models to predict the future closing stock price trends of NIFTY 50. Then, they compared the achieved results using four regression metrics (MSE, RMSE, MAE and R2). The process of selecting features from financial data and tuning the hyperparameters of the models was conducted through manual tests.

Kumar *et al.* (2022) proposed a traditional time-series model, Auto Regressive Integrated Moving Average (ARIMA), combined with a neural network model (LSTM) to predict the stock market. For the task of hyperparameter selection, the Artificial Bee Colony (ABC) algorithm using differential evolution (DE) was applied. Their proposed model was tested on various financial datasets, such as the NASDAQ index, and benchmarked against other models like ARIMA.

Zouaghia *et al.* (2023) applied a hybrid deep learning (DL) model to predict the stock index of NASDAQ. They combined a CNN with four architectures of RNNs (GRU, Bidirectional GRU, LSTM, and Bidirectional LSTM). They used a 1D-CNN model to extract automatically the more accurate features from historical stock data. Then, the output of the 1D-CNN model was used as input to RNNs to predict the future stock index. For the hyperparameter optimization, they used a manual search strategy. To evaluate their models, they applied six metrics: ET, MSE, RMSE, MAPE, MAE and R^2.

Proposed Approach

In this section, we detail our proposed approach based on the AutoCNN model. This framework is used to predict future stock indices during periods of uncertainty and fear, especially during turbulent times due to external factors. The general architecture of AutoCNN is detailed in Figure 1. This framework is composed of a cycle, which is primarily based on three stages: (1) CNN for automatic feature extraction; (2) a HGS method combined with a second CNN for stock index prediction; and (3) the step of evaluation and comparison. Our framework performs many iterations to screen which is the best CNN model topology.

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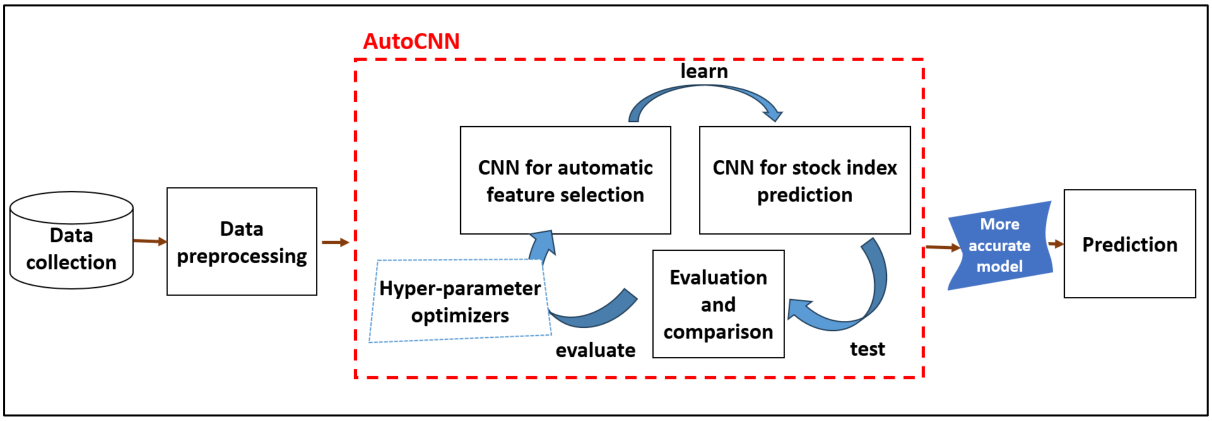

Figure 1. The general architecture of the AutoCNN framework

The proposed solution leads to assistance to financial decision makers to acquire a global vision about the actual and future fluctuations of stock indices during crisis periods and, then, to make the right decision with more confidence under uncertainty. AutoCNN is benchmarked against three other implemented neural networks (LSTM, GRU, and SRNN) in addition to existing models in the literature. The components of our framework are described below.

Stage 1: CNN for automatic feature extraction

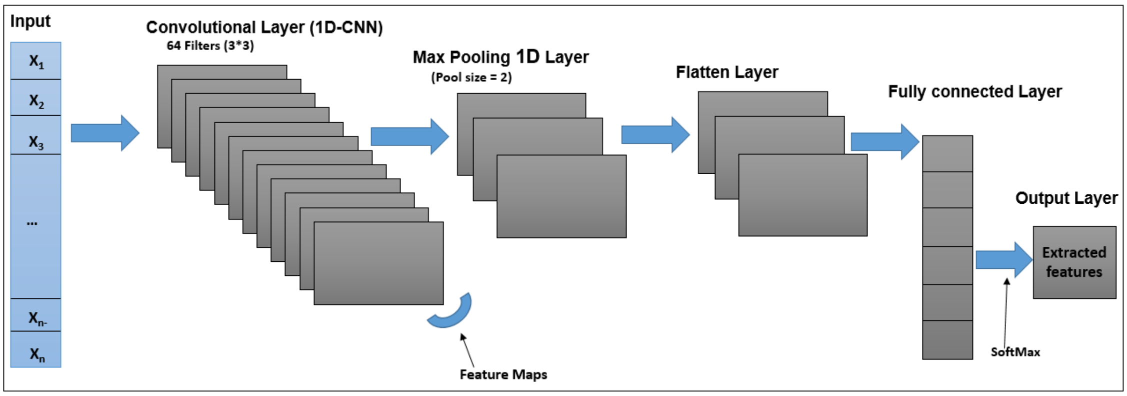

Figure 2. The architecture of 1D-CNN model for automatic feature extraction

The process of Feature Extraction is one of the most challenging problems in deep learning modelling, especially in time-series forecasting. This issue is tackled by several researchers, who proposed various approaches. The CNN model is proposed by Krizhevsky *et al.* (2017) to extract features from images but, in this work, we extract features from financial data. Time-series prediction is considered one of the most frequently applied uses of one dimensional (1D) CNN in practice (Markova, 2022). In this work, we choose the architecture of 1D-CNN for the step of automatic feature extraction. This configuration has strong capabilities to learn, understand and extract features from the input stack variables, owing to its hierarchical architecture and the nature of stock price data. Our choice is based on the work of Zouaghia *et al.* (2023). Figure 2 explains this architecture.

Stage 2: An optimized CNN for stock index prediction

In AutoCNN, the CNN model is not only used for the step of automatic feature extraction, but also we undertake stock index prediction using this model. According to Vargas *et al.* (2017) and Wu *et al.* (2021), the CNN model has shown good abilities in stock price prediction. Further, to perform this task, the output of the first 1D-CNN model, which is the extracted features, is used as input for a second optimized 1D-CNN model (HGS-CNN).

Hyperparameter optimization is a crucial step in the process of training machine-learning models. This step specifies many aspects of the learning algorithm and the model's architecture, such as the learning rate, the number of units in hidden layers, the optimizer and number of filters in the CNN model. In AutoCNN, we adopt the HGS algorithm for automatic optimization of its hyperparameters. The principle of this method is successive halving processes (Pedregosa *et al.*, 2011). In this work, we adopt this method to optimize hyperparameters of the considered neural network-based models for several reasons, namely:

1. It has been rarely applied in scientific research works (Jung *et al.*, 2023) and it has shown strong ability in the task of tuning optimized hyperparameters.
2. The evidence behind this choice is its computational efficiency, time saving, adaptability to high-dimensional search spaces, robustness to noisy metrics, and effective balance between exploration and exploitation.

Stage 3: Evaluation and comparison

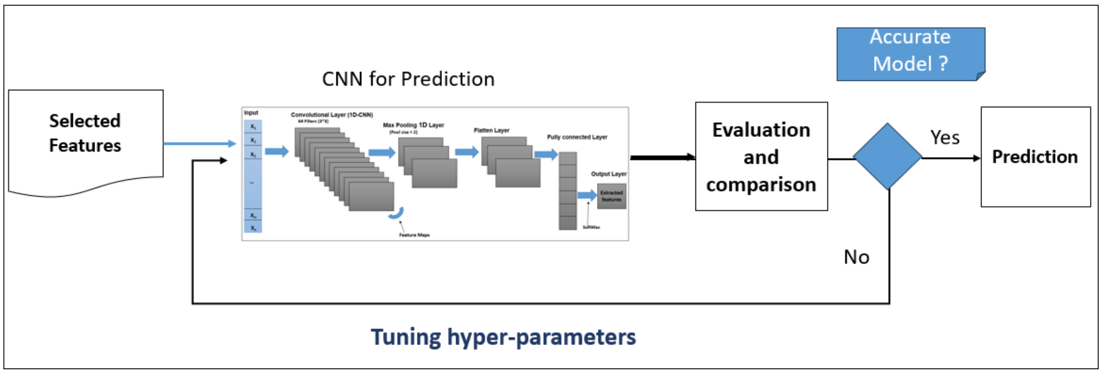

Figure 3. Hyperparameter optimization process in AutoCNN framework

For the evaluation and comparison task, we use various measures to obtain a more accurate model. Figure 3 details this process: after n iterations, if the considered measure does not satisfy a threshold of error acceptance, a new iteration of hyperparameter tuning is conducted using the HGS algorithm. The final output of the AutoCNN framework is a more accurate and stable model and the predicted stock index values. If the model generated accurate predictions, it is recommended to be applied by investors.

Experiments and Results

In this section, we present the datasets used to test AutoCNN. The experiments conducted and the achieved results are discussed, referring to various metrics.

Experimental environment

Our experiments are conducted on a computer with the following characteristics: Intel Core i7 7th Gen 2.8 GHz, 32 GBs of RAM, and the operating system of Microsoft Windows 10 Professional. The implementation has been made in Python programming language based on various libraries. The main used libraries are: (1) *Sklearn* to process data and select metrics; (2) *Keras* to select neural networks models and layers; (3) *Tensorflow* to build, train, and deploy deep learning models; (4) *Time* to compute the execution time of each model; (5) *Matplotlib* to create static and interactive visualizations; and (6) *statsmodels* to conduct a statistical test, like the ADF and the stepwise tests, etc.

Financial data description and analysis

Visualizing financial data is a powerful technique that allows us to foresee a clear perspective of stock price changes in response to certain events or external factors, and data analysis helps us to choose the more adequate model for the task of stock market index prediction.

Data gathering

In this paper, we consider two datasets of two different stock exchanges: (1) Shanghai Stock Exchange (SSE) index; and (2) National Association of Securities Dealers Automated Quotations (NASDAQ) index, covering the period between 2018 and 2023. Data are collected from Yahoo Finance Website and include seven variables as described in Table 1.

Table 1. Parameters of the used financial data

Variable	Description
Date	The trading date
Open	The opening price of the stock, at the start of a trading day
High	The highest price of the stock, during a trading day
Low	The lowest price of the stock, on a trading day
Close	The closing price of the stock, at the end of a trading day
Adj Close	The closing price after adjustments: the stock's value after distributing dividends
Volume	The amount of Stock traded in the market during a period

Data analysis

Researchers have proven that neural networks are suited to non-stationary data (Reid *et al.*, 2014; Kurle *et al.*, 2019 ; Zhou *et al.*, 2021). In this situation of non-stationarity, stock price

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data are hard to be predicted and CNNs are suitable for capturing insights for modelling short-term dependencies in data.

A statistical test is used to analyse the stationarity in time series of our two stock indices. To analyse the stationarity of the predicted variable (closing price), the Augmented Dickey-Fuller (ADF) test is applied. The ADF test is a common type of statistical test called a unit root test. It is used to identify the presence of a unit root and transform the series into a stationary state (Dadhich *et al.*, 2021). It is based on two hypotheses (H_0 and H_1):

- Null Hypothesis (H_0): The time series has a unit root, indicating that it is non-stationary.
- Alternative Hypothesis (H_1): The time series does not have a unit root, indicating that it is stationary.

The null hypothesis is evaluated through a calculated t-statistic, which is calculated by the formula as seen in the paper of Reddy (2019). If the t-statistic calculated is bigger than the critical value, we accept the hypothesis H_0 and data are non-stationary. On the other hand, if the t-statistic calculated is less than the critical value, we reject the H_0 and data are stationary. Additionally, "P-value" is also used to reject or accept the H_0: if the "P-value" is less than 0.05 ($P<0.05$), we reject the H_0; and vice-versa. Table 2 shows the generated values of the test ADF for both SSE and NASDAQ indices.

Table 2. ADF test

SSE index				NASDAQ index			
		t-statistic	Prob.*			t-statistic	Prob.*
ADF test statistic		-1.695	0.748	ADF test statistic		-1.487	0.540
Test critical values	1%	-3.435		Test critical values	1%	-3.435	
	5%	-2.863			5%	-2.863	
	10%	-2.568			10%	-2.568	

It is shown from Table 2 that the calculated "t-statistic" value is greater than critical values at 1%, 5% and 10% levels of significance. Therefore, we can conclude that data of SSE and NASDAQ indices are non-stationary. Further, the "P-value" is also greater than 0.05. So, in our case, we do not reject the H_0: this means that data has a unit root and is non-stationary.

Reaction of the stock markets to the last two crises

In this part, we analyse the impact of the last two crises (the international health crisis of the COVID-19 pandemic; and the international conflict between Russia and Ukraine) on the variation of prices in stock markets, because our AutoCNN model is trained on data covering these two major events, contributing to improved generalization, its adaptability, and robustness. Therefore, AutoCNN can be able to predict accurately future stock indices during uncertainty.

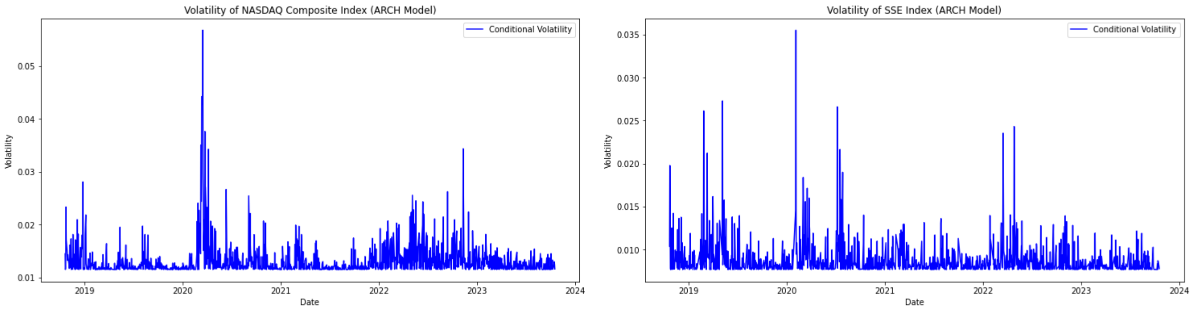

Figure 4. The calculated volatility of NASDAQ and SSE indices

First; an ARCH(1) model, which is a type of autoregressive conditional heteroskedasticity model, is designed to capture time-varying volatility in financial time-series data. Figure 4 visualizes how the volatility changes over different periods from October 2018 until October 2023.

The volatility provides insights into risk during crisis periods and into potential trading opportunities. Further, high volatility might represent increased risk but also, in some cases, it indicates potential profit opportunities for traders; low volatility reflects stability. The volatility of stock prices is considered as a fear gauge of investors. From Figure 4, it is clear that the stock prices of NASDAQ and SSE indices are more volatile during the periods of the global health crisis (COVID-19 pandemic) especially between 2020 and 2021. Additionally, since February and March 2022, it is seen that the variation is also more pronounced due to the recent geopolitical crises, such as the Russian, Ukrainian, European and American conflicts. Thus, due to these two major factors, investors become more disturbed and cannot easily take the right decisions (to buy or sell a given stock), which explains not only the rapid fluctuations and shocks in stock prices but also the suffered losses as seen in Figure 5 (represented by negative values). In this case, investors and financial analysts need help in making financial decisions in an uncertain environment.

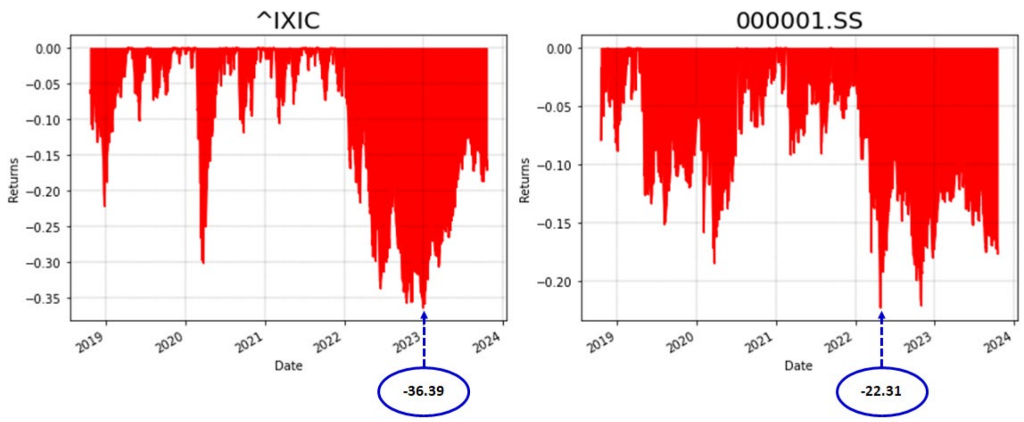

Figure 5. The calculated drawdown falls for NASDAQ and SSE indices

The drawdown for a stock market index represents the peak-to-trough decline in the index's value during a specific period. It measures the maximum percentage decrease from the highest point to the lowest point before a new peak is achieved. NASDAQ (^IXIC) and SSE (000001.SS) indices absorbed several losses, and the maximum losses are 36.39% and 22.31%, respectively, for NASDAQ and SSE indices, as shown in Figure 5.

Evaluation criteria

AutoCNN is evaluated using the Execution Time (ET) metric, four regression evaluation metrics — Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) — and the Coefficient of Determination (R^2). The formulas for calculation are shown in Table 2.

Table 3. The evaluation metrics used

Metric	Formula
ET	Execution Time =Current time - Start time
MSE	$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2$
RMSE	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$
MAE	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert x_i - y_i\rvert$
MAPE	$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\lvert x_i - y_i\rvert}{x_i}$
R^2	$R^2 = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$

Note: n is the number of data points in the test set, x_i is the actual value, $\overline{x}$ is the mean value of the actual values, and y_i is the predicted value.

MSE, RMSE, MAE, MAPE and R^2 metrics are used for model evaluation after the model has been trained. Once the implemented models are trained, these metrics are used to assess how

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well the models generalize to new, unseen data (the principle of supervised machine learning models). These metrics provide a quantitative measure (Zouaghia *et al.*, 2023) of the AutoCNN's performance on subset test data. Moreover, metrics like MAPE provide insights into the percentage error, which can be more interpretable from a business perspective. This is particularly important in financial applications where understanding the relative size of errors is valuable.

Smaller values of ET, MSE, RMSE, MAE and MAPE designate a better result. However, greater values of R^2 indicate a better result. Further, concerning the ET metric, it measures the cost of each implemented model in terms of time (seconds) that depends on different components, such as the size of the used dataset, the complexity of each model, and the power of the hardware used for our experiments.

Additionally, a stepwise multiple testing method (a statistical technique) is used to conduct multiple statistical tests of AutoCNN to assess various aspects of model's performance. Figure 6 shows all the steps used to evaluate our model using this statistical method. In step 8, the Holm method is selected, which is a step-down procedure that adjusts the significance level based on the order of hypotheses, for adjusting p-values to control the family-wise error rate.

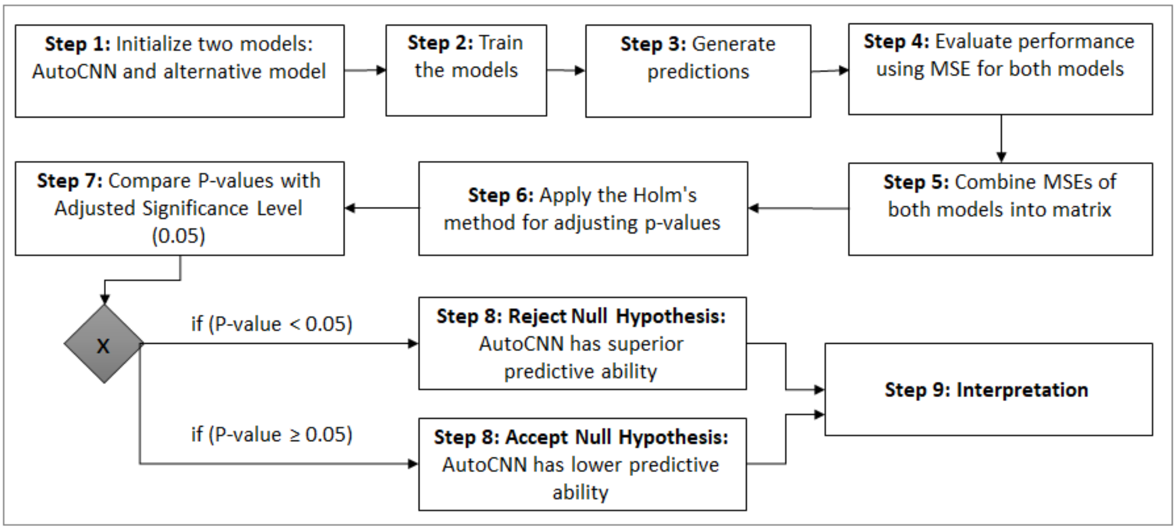

Figure 6. Flowchart for the stepwise multiple testing method

Auto-generated model parameters

The chosen parameters for AutoCNN, used in common for all comparative models, are detailed in Table 3.

Table 4. Parameters common to all models

Parameter	Value
Prediction frequency	Daily
Dataset	SSE index and NASDAQ Composite index

Parameter	Value
Data specification	From 2018 to 2023
Normalisation	[0-1]
Input features	Automatic selection using CNN
Target variable	Close price
Training: Testing	80%: 20%

The structure of the AutoCNN model is comprised of ten layers (5 layers in the task of automatic feature extraction; and 5 layers in the task of stock index prediction). Additionally, changes in data have an impact on the robustness and stability of the model, because AutoCNN is trained on data containing sensitivity periods, like the international COVID 19 pandemic health crisis especially during the year 2020, or the last geopolitical crisis of the Russia-Ukraine conflict during 2022. Our models are trained through these changes (correlation) in stock data in order to be able to predict future stock indices in similar cases using AutoCNN.

Results and discussion

We provide comparative results between AutoCNN and other benchmarked models: LSTM, GRU, SRNN, and ARIMA. Results are summarized in Tables A1 and A2 (Appendix A), where the best performance results are marked in bold for each stock market index per metric. In Tables A1 and A2, it is clearly seen that AutoCNN outperforms the three benchmarked neural network models (CNN-LSTM, CNN-GRU, and CNN-SRNN). For the SSE index, AutoCNN generated 0.00001, 0.003, 0.002, 0.4%, and 0.998, respectively, for the MSE, RMSE, MAE, MAPE, and R^2 indicators. For the NASDAQ Composite index, AutoCNN generated 0.00001, 0.004, 0.003, 0.53%, and 0.999, respectively, for the MSE, RMSE, MAE, MAPE, and R^2 indicators. Moreover, concerning the execution time metric, it is seen that AutoCNN is trained with the minimum time, less than two seconds for both the stock indices. AutoCNN did not only outperform the implemented neural network models, but also it achieved superior performance compared to the traditional ARIMA model (Lv *et al.*, 2022; Kumar *et al.*, 2022).

Additionally, Figures B1, B2, B3 and B4 (Appendix B) plot the real and predicted values of SSE and NASDAQ indices using neural network models based on the test set of data. The blue line indicates the actual stock prices, while the red and orange lines represent the predicted stock prices. In these four figures, it is shown that the AutoCNN model performs better than the other models considered for comparison; especially, Figure B1 shows visually that the predicted values and the real values of stock prices are very close. AutoCNN was successful in capturing the pattern in all the periods of the data.

To compare the implemented models in more detail, Figures C1, C2, C3, C4, C5 and C6 (Appendix C) provide a graphical visualization of the results obtained for each metric to evaluate and compare the performance of each model. From these Figures, it is clear that

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AutoCNN generates the lower error rates in terms of MSE, RMSE, MAE, R^2, and MAPE; and is trained in a very short time compared to other networks considered for comparison.

It is observed through our experiments that AutoCNN always generates the superior prediction results in the Chinese context (SSE index), as well as in the American context (NASDAQ Composite index), compared to the other benchmarked models. The theoretical foundation behind achieving different results with CNN and in a Chinese context or an American context, in comparison to other research works in the literature, is that we did not use the same configuration or the same hyperparameter values, because this process is handled automatically. AutoCNN is able to detect correlations between stock price variations across temporal dependencies in CNN.

Additionally, referring to the stepwise multiple testing procedure of Romano & Wolf (2005) and in order to prove the superior predictive ability of AutoCNN using a statistical method, we benchmarked our AutoCNN model against a very popular and applied machine learning model (Support Vector Regression, SVR) in prediction. In this paper, SVR shows strong abilities in the task of stock index prediction (Zheng *et al.*, 2005). In our experiments, the SVR model is trained on the same data (NASDAQ index and SSE index), then it is evaluated alongside our AutoCNN model for predicting the stock prices. Through our experiments, the adjusted p-values for the model comparisons are provided in Table A3 (Appendix A).

In Table A3, for the NASDAQ Composite index, the Adjusted p-value= 3.16e-05<0.05: this provides strong statistical evidence to reject the null hypothesis, indicating a significant difference in predictive ability between the AutoCNN model and the alternative model (SVR). There is the same interpretation for the results using the SSE index. For the SSE index data, the adjusted p-value=2.03e-05<0.05: this indicates strong evidence against the null hypothesis — the AutoCNN model is deemed to have a significantly different predictive ability compared to the SVR model.

To summarize, AutoCNN is experimented on with two different stock index datasets, from different countries, and it is proven that this model is robust and stable, because, when we change the input, it always generated superior results. We argue that this hybrid auto-generated model can be reproduced on other indices or financial time series.

Overall, AutoCNN is able to better understand the dynamical variations in daily SSE index and NASDAQ index that are caused by external factors, especially in crisis periods. AutoCNN generated results in the task of stock index prediction that are superior to those from other implemented neural networks (SRNN, GRU and LSTM), due to its ability to effectively capture local patterns and temporal dependencies within the financial data. It excels at feature

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extraction, automatically learning hierarchical representations of input data, which is beneficial for identifying short-term trends and specific features influencing stock price movements. Additionally, AutoCNN requires less preprocessing and can be computationally more efficient, contributing to its superior performance in the stock prediction scenario. Thus, the hybridization of the halving grid search technique with a CNN has demonstrated robust capabilities in optimizing model hyperparameters effectively, with reduced computational cost compared to exhaustive methods such as the grid search technique, which is greedy in terms of resource use.

Limitations of the Proposed Approach

AutoCNN can be considered as a financial decision support system that can help investors or financial institutions. It aims to enhance the decision-making processes in the context of stock index prediction and it involves several key aspects, all of which contribute to more effective and successful investment strategies, such as:

1. Informed decision-making;
2. Risk mitigation;
3. Optimized Timing;
4. Adaptation to Market Dynamics.

Nevertheless, AutoCNN is not without limitations. One notable constraint is the inherent difficulty in capturing the dynamic and intricate nature of financial markets solely through the analysis of historical price charts (combining fundamental analysis with artificial intelligence techniques). AutoCNN may struggle to discern the complex temporal dependencies and subtle market trends that influence stock prices. The explainability of the AutoCNN model represents a prominent issue for future work. Moreover, stock prices are influenced by a multitude of factors, such as economic indicators and market sentiment, which may not be adequately represented in the input data for the AutoCNN model. Therefore, while this approach offers a promising avenue for stock price prediction, it is crucial to acknowledge these limitations and consider complementary approaches, such as incorporating fundamental analysis or sentiment analysis, to enhance the model's robustness and reduce the risk of overestimating its predictive capabilities.

Conclusions and Orientation for Future Research

Recent technological advances, such as the deep learning approach, contribute to digital transformation of the economy sectors, including finance. Deep learning has become widely applied and it is considered a motive power in the current digital economy. The purpose of this paper is to use the automated deep learning (AutoDL) technique to propose an intelligent financial decision-support system to investors, to help them to make accurate decisions on financial investment during periods of uncertainty.

Deep learning models, and especially CNN, are applied in this research work to propose a robust and stable solution, named AutoCNN, which is used in three steps, namely: (1) CNN for Automatic Feature Extraction; (2) HGS algorithm hybridized with CNN for stock price prediction; and (3) Evaluation and comparison. AutoCNN is firstly benchmarked against five models (LSTM, GRU, SRNN, ARIMA, and SVR), using five regression metrics (MSE, RMSE, MAE, R^2, and MAPE) , an execution time (ET) metric, and a statistical method (stepwise multiple testing procedure). After conducting several experiments, we have realized that the proposed AutoCNN can stably predict the stock index prices under uncertainty. Therefore, we recommend it to be used by investors, without demand for expert knowledge because all the process is automated. The benefits from this work are to prove the effectiveness of applying neural network architectures to offer reliable predictions for financial decision makers in the digitalised economy during crisis periods.

For future work, we propose an extension of this paper by including other emergent neural network architectures, such as the Spiking Neural Networks (SNNs), and involving other stock exchange indexes.

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Appendices

In this section, we include Tables and Figures concerning the comparison of results.

Appendix A

Table A1. Comparison of validation metrics of AutoCNN against benchmarked models for SSE index

Model		Metrics				
	MSE	RMSE	MAE	R^2	MAPE (%)	ET (second)
AutoCNN	**0.00001**	**0.003**	**0.002**	**0.998**	**0.4%**	**1.63**
LSTM	0.00008	0.009	0.006	0.986	1.1%	21.4
GRU	0.00008	0.009	0.007	0.985	1.3%	20.5
SRNN	0.00007	0.008	0.007	0.987	1.2%	8.09
ARIMA (Lv *et al.*, 2022)	-	36.981	25.102	0.9690	0.8%	-

Table A2. Comparison of validation metrics of AutoCNN against benchmarked models for NASDAQ index

Model		Metrics				
	MSE	RMSE	MAE	R^2	MAPE (%)	ET (second)
AutoCNN	**0.00001**	**0.004**	**0.003**	**0.999**	**0.53%**	**1.8**
CNN-LSTM	0.00003	0.006	0.003	0.997	0.54%	22.8
CNN-GRU	0.00004	0.006	0.004	0.997	0.67%	21.5
CNN-SRNN	0.00007	0.008	0.006	0.995	0.99%	8.4
ARIMA (Kumar *et al.*, 2022)	-	20.438	-	-	1.43%	-

Table A3. The stepwise multiple testing method applied to AutoCNN

Results generated by the stepwise multiple testing method		
	SSE index	NASDAQ index
AutoCNN vs SVR	2.03e-05	3.16e-05

Appendix B

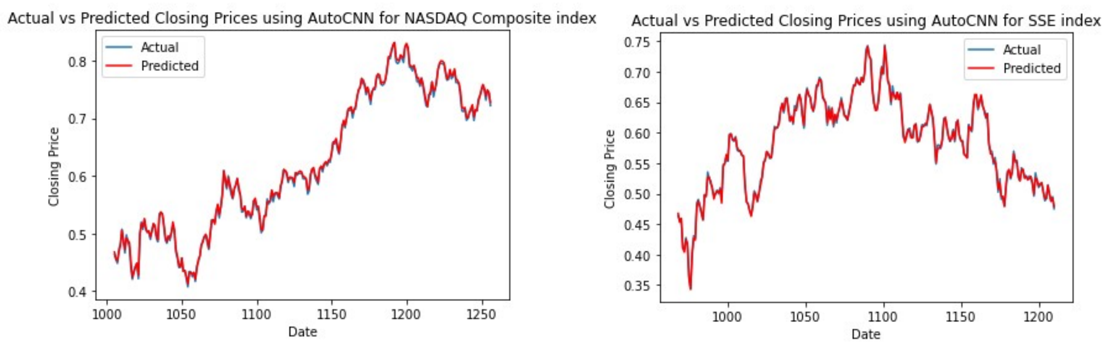

Figure B1. Real value vs Predicted value using the AutoCNN model

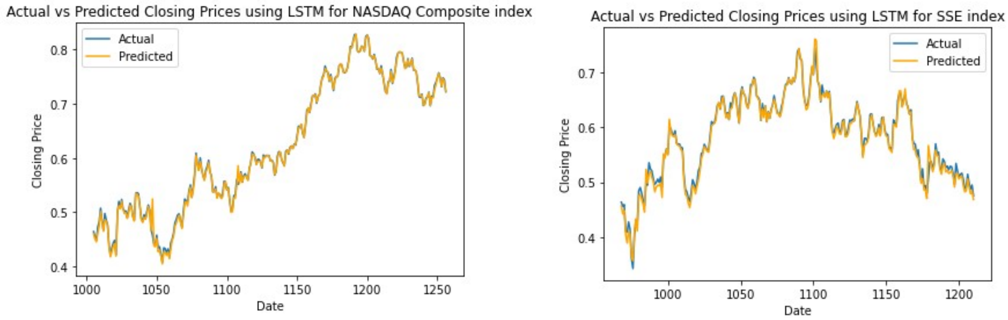

Figure B2. Real value vs Predicted value using the LSTM model

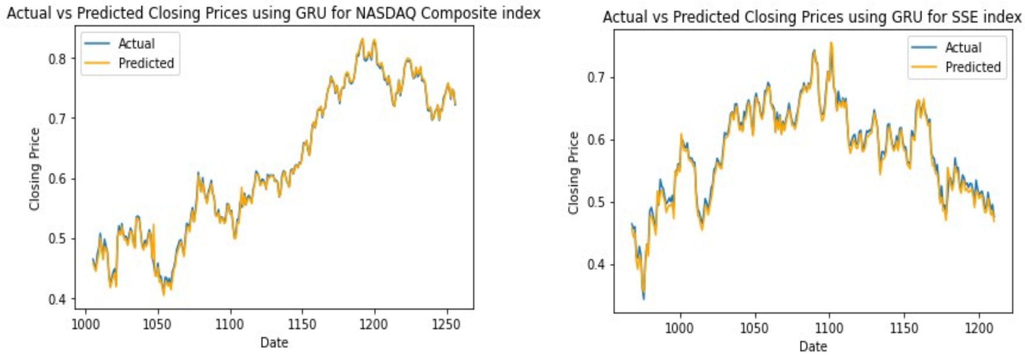

Figure B3. Real value vs Predicted value using the GRU model

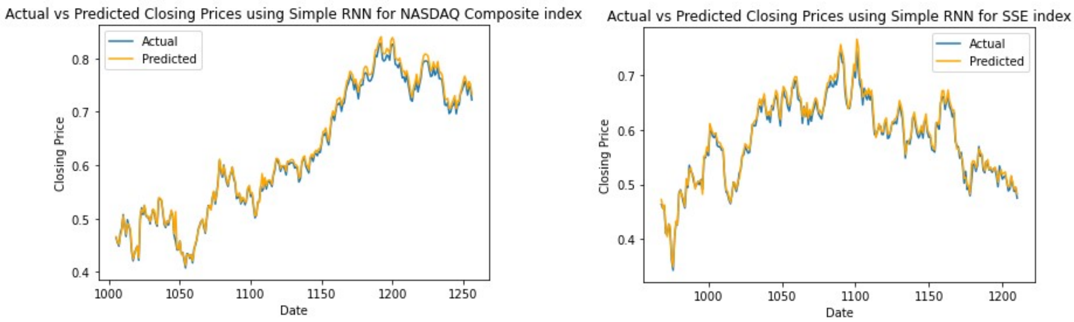

Figure B4. Real value vs Predicted value using the SRNN model

Appendix C

In Figures C1, C2, C3, C4 and C5, the y-axis represents the error rates generated by the models considered, while the x-axis denotes the name of each implemented model per dataset. However, for Figure C6, the y-axis represents the time consumed by each model during the training phase and the x-axis denotes the name of the model.

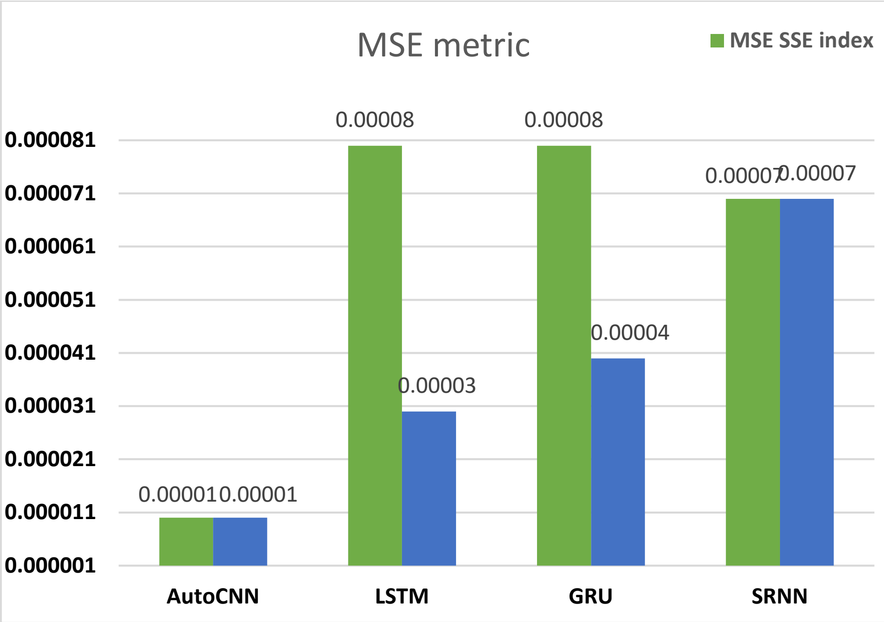

Figure C1. MSE comparison of the implemented models

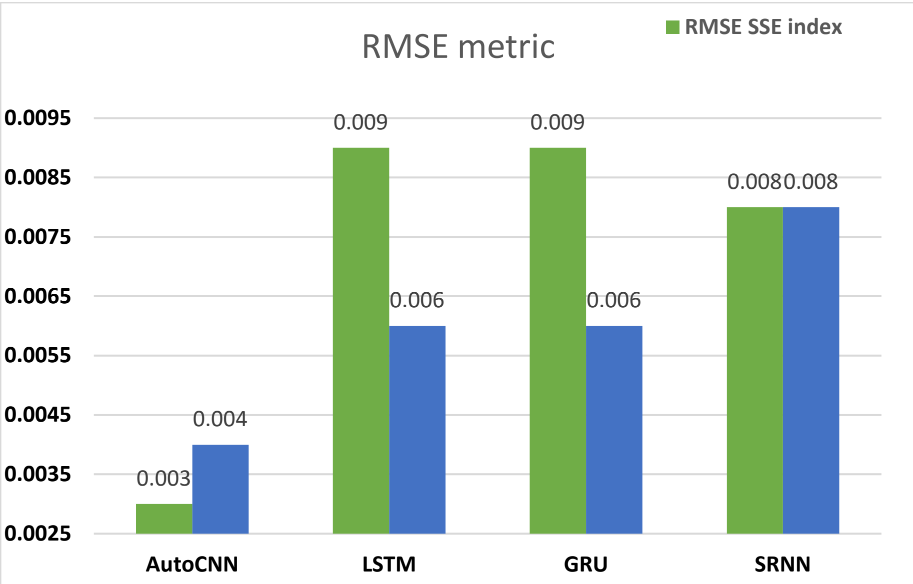

Figure C2. RMSE comparison of the implemented models

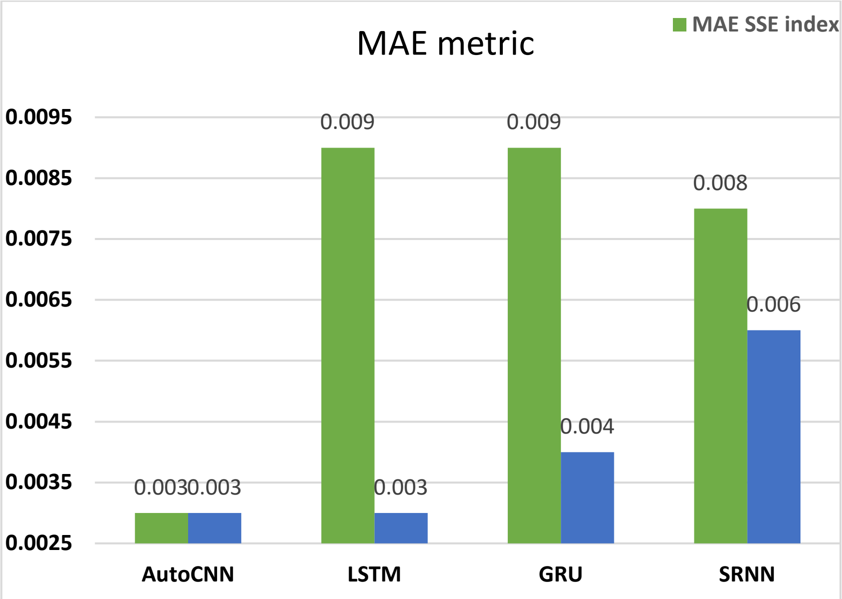

Figure C3. MAE comparison of the implemented models

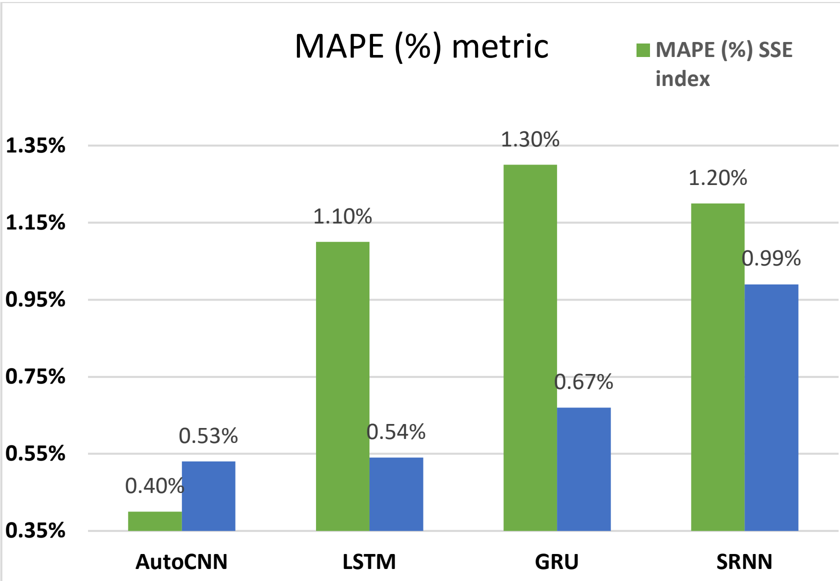

Figure C4. MAPE comparison of the implemented models

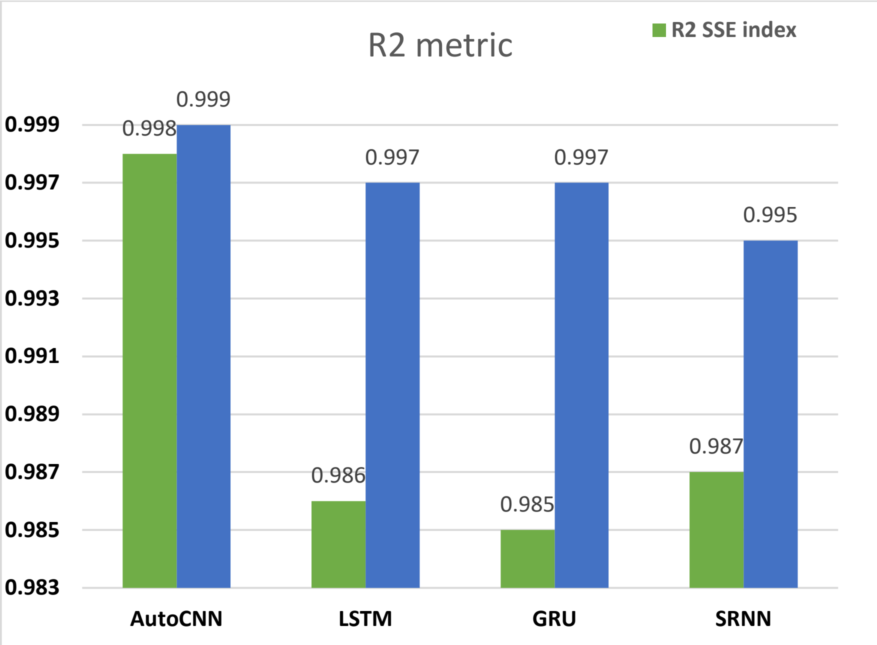

Figure C5. R^2 comparison of the implemented models

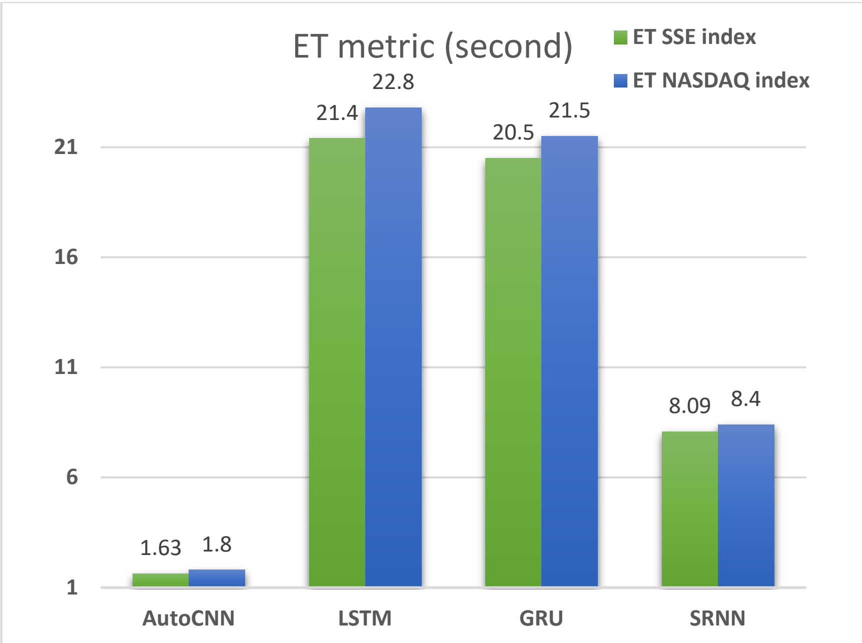

Figure C6. Execution Time comparison of the implemented models

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Development of Digital Financial Inclusion in China's Regional Economy: Evidence from Panel Threshold Models

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Abstract: This study aims to investigate the effect of digital financial inclusion and air pollution on economic growth for 31 Chinese provinces between 2003 and 2022 using Panel Threshold Auto-Regressive (PTAR) and Panel Smooth Transition Auto-Regression (PSTAR) models. The results show that there is a nonlinear link between digital financial inclusion and economic growth in China. For PTAR, the LnDFII thresholds are 4.264 (i.e., DFII = 71.094), and for PSTAR are 4.563 (i.e., DFII = 95.871). Below these thresholds, digital financial inclusion significantly boosts economic growth by 0.061 and 0.063 in the PTAR and PSTAR models, respectively. However, above these thresholds, the positive impact diminishes, with coefficients dropping to 0.015 and 0.004 in the PTAR and PSTAR models, respectively. Additionally, both models indicate that digital financial inclusion positively affects reducing air pollution, thereby potentially fostering economic growth. Hence, authorities should strategically implement digital technologies and strengthen collaborative efforts at the regional level to maximize these benefits.

Keywords: Digital Financial Inclusion, Regional Economy, Panel threshold model

Introduction

Digital financial inclusion influences consumption, income, and development inequality. For instance, Liu *et al.* (2021) and Li *et al.* (2020) conclude that digital finance has a significant

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role in promoting household consumption and, consequently, economic growth. Moreover, inclusive digital finance changes the consumption patterns of residents by boosting their income, enhancing convenience, and improving mobility, especially in rural regions (Yu *et al.*, 2022). In other studies, Yu & Wang (2021) and Xu *et al.* (2023) proved the effectiveness of digital finance in alleviating regional development disparities and bridging the income gaps between urban and rural areas. All these are confirmed by our results, which show that digital financial inclusion has a positive and significant impact on economic growth in China.

To explain further, when we talk about digital financial inclusion, we are referring to the extent to which individuals and industries in a given area can benefit from digital financial services like mobile banking, online payments, or digital lending. Regional economy, on the other hand, relates to the overall economic development and expansion within a specific geographic area.

According to a report by the China Financial Inclusion Institute (CAFI) (2018), digital financial inclusion (DFI) has impressive penetration rates, enabling a large portion of previously unbanked or underbanked activities to easily access financial services by time or space. Over the past decade, DFI has experienced rapid growth with the phenomenal growth of digital technology, especially financial technology (FinTech), and the popularity of mobile communications and smartphones in China.

Another report from the Peking University Digital Finance Institute (PKU-DFII) showed that the median Digital Financial Inclusion Index (DFII) across Chinese provinces (Feng *et al.*, 2019) increased from 33.6 in 2011 to 294.3 in 2011–2018. This is where wireless fifth-generation networks, cloud computing and data storage centres, and other large-scale infrastructure initiatives are driven by China's rapid digitization (Cheng *et al.*, 2021). Due to their large energy consumption, these infrastructure projects significantly worsen air pollution (Dong *et al.*, 2021).

Although economic growth, industrial structure, energy consumption patterns, and environmental policies are considered important factors affecting China's air quality, the digital economy boom can be regarded as a new mechanism to reconstruct China's economic and environmental development (Guo *et al.*, 2021; Yang *et al.*, 2022b; Zeraibi, Jahangir *et al.*, 2023; Jiang *et al.*, 2022; Ren *et al.*, 2023). Moreover, the air pollution level in China showed a decreasing tendency from 2003 to 2022, which is consistent with the country's dropping sulphur dioxide (SO2) and particulate matter ($PM_{2.5}$) per 10 Km^2 (see Figure 1). Furthermore, the digital economy grew quickly, and the value added to China's digital economy expanded from 9.5 to 50.2 trillion yuan (from about 1.31 trillion U.S. dollars to 7.25 trillion U.S. dollars) between 2011 and 2022. Thus, air pollution levels and the digital economy are related in this country.

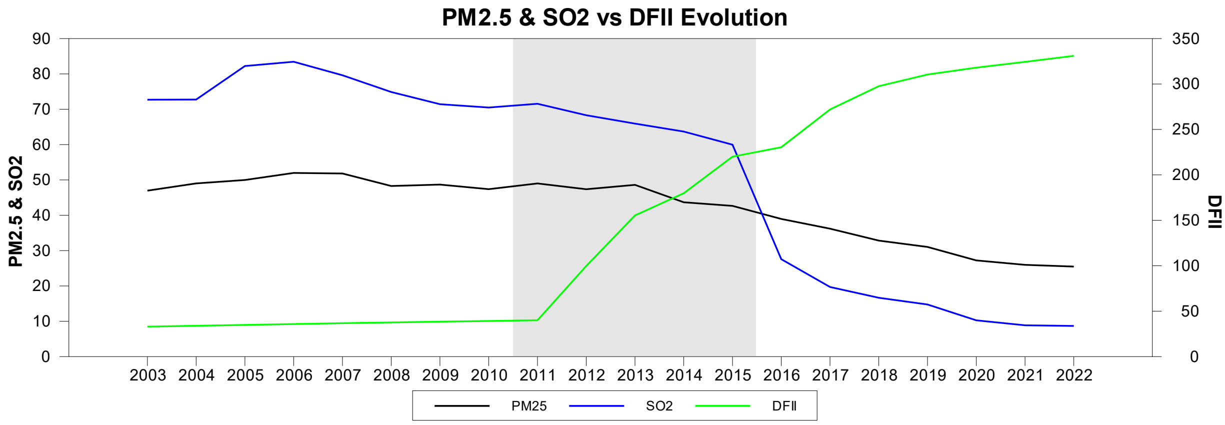

Figure 1. Evolution of DFII and the indexes of air pollution in China (per year)

In particular, existing literature shows that the digital economy can reduce environmental pollution by promoting economic growth (Higon *et al.*, 2017; Li *et al.*, 2021; Jahanger *et al.*, 2022). In addition, digital economy development can lead to the effective reallocation of economic resources among different economic sectors, thereby affecting environmental quality.

With this in mind, it is important to examine how China's digital economy affects economic growth. To evaluate this impact on province-level air pollution in China, this study employed panel threshold models for 31 Chinese provinces from 2003 to 2022. It is possible that this research can have unknown disruptions to China's future efforts to reduce pollution. This is the precise research issue that this study looked into: how do environmental factors (air pollution, sulphur dioxide, and nitrogen oxide) relate to China's regional economy when digital financial inclusion improves from lower to higher levels?

Our analysis has two main contributions. Firstly, we investigate the nonlinear impacts of digital financial inclusion on economic growth in China using dynamic panel threshold models (PTAR and PSTAR). We find that digital financial inclusion has a modest yet significant positive effect on growth below certain threshold levels. These findings contribute to the understanding of how digital financial inclusion can stimulate economic growth in different regional contexts (Yu *et al.*, 2022; Ben Abdallah *et al.*, 2023). Secondly, the study also examines the co-effects of a mix of environmental factors (SO_2, NOX, and $PM_{2.5}$) on digital finance inclusion in China. It concludes that digital financial inclusion contributes positively to reducing air pollution (Liu *et al.*, 2021; Li *et al.*, 2020). This aspect of the research is particularly important as it links financial inclusion with environmental sustainability, offering insights into how digital financial tools can support broader socio-economic goals, including environmental protection.

The remaining sections of the essay are structured as follows: The pertinent literature is briefly reviewed in the second section. The data and methodology used in this investigation are described in the third section. The empirical analysis and discussion are presented in the fourth section. The research is concluded in the fifth section, which also addresses the consequences for policy and identifies potential future research areas.

Theoretical Overview and Hypothesis Development

As soon as the notion of digital financial inclusion was proposed in China, a large number of theoretical and empirical studies were carried out to determine its impact on economic growth. According to most researchers, the development of digital financial inclusion promotes economic expansion. For example, Lv *et al.* (2021) and Yang *et al.* (2022a) revealed that digital financial inclusion significantly promotes economic growth, but there are also slight regional differences in spatial correlation and promotion effects.

Another study by Ma & Jiang (2024) explores the impact of DFI on the investment efficiency of small and medium-sized enterprises (SMEs) in China from 2011 to 2020. They find strong evidence that the development of DFI improves the investment efficiency of underinvested SMEs. However, this effect is not observed for overinvested SMEs. In addition, they show that the positive impact of DFI on underinvestment is more pronounced among SMEs with weaker financial conditions or weaker industry competitiveness.

Other scholars (He *et al.*, 2021; Yang *et al.*, 2022a) believe that regional economic growth and digital financial inclusion have a non-linear relationship with the existence of a threshold effect. Above a certain threshold of development, the positive impact of digital financial inclusion on economic growth can be reinforced.

In addition, Zhan (2018) proved that inclusive digital finance improves the quality of economic growth but would have a negative effect on the level of economic growth. Thus, this relationship exhibits a U-shaped and an inverted-U-shaped relationship, respectively.

On the other hand, the impact of digital financial inclusion on the environment has not been thoroughly studied. The per-capita gross domestic product (GDP) has an inverted U-shaped relationship with environmental pollution, which is called the Environmental Kuznets Curve (EKC) (Grossman & Kruege, 1995). EKC believes that economic growth usually leads to an increase in environmental pollution, but, after the introduction of effective environmental controls, additional economic growth will reduce environmental costs (Dong *et al.*, 2018; Zhang *et al.*, 2020; Fang *et al.*, 2021).

In addition, as regional economic growth momentum increases, China's political leaders can limit the flow of resources to polluting companies, prudently guide capital flows to green industries, and increase corporate enthusiasm for green technologies (Ding *et al.*, 2022). This can solve an issue with digital finance inclusion and achieve a sustainable economy. In the same era, the findings of Song & Majeed (2023) confirm that digital financial inclusion, ICT, and GDP are critical to promoting short- and long-term renewable energy production. Green investment, environmental governance, and carbon emissions also have a significant positive impact on long-term renewable energy production.

Thus, the following hypotheses are put forth in this study:

H1: A combined policy of environmental protection (NOX, SO2, and PM2.5) and digital financial inclusion have a corroborated positive effect on regional economic improvement.

H2: The level of air pollution has an impact on how the expansion of digital financial inclusion moves regional economic growth.

H3: The extent of air pollution and GRP co-movement depends on the level of progress in digitalized financial inclusion.

H4: The DFII at lower and higher levels impacts GRP differently.

By taking into account the studies mentioned above on the effects of environmental legislation, regional economic growth, and digital financial inclusion, the framework depicted in Figure 2 can be obtained.

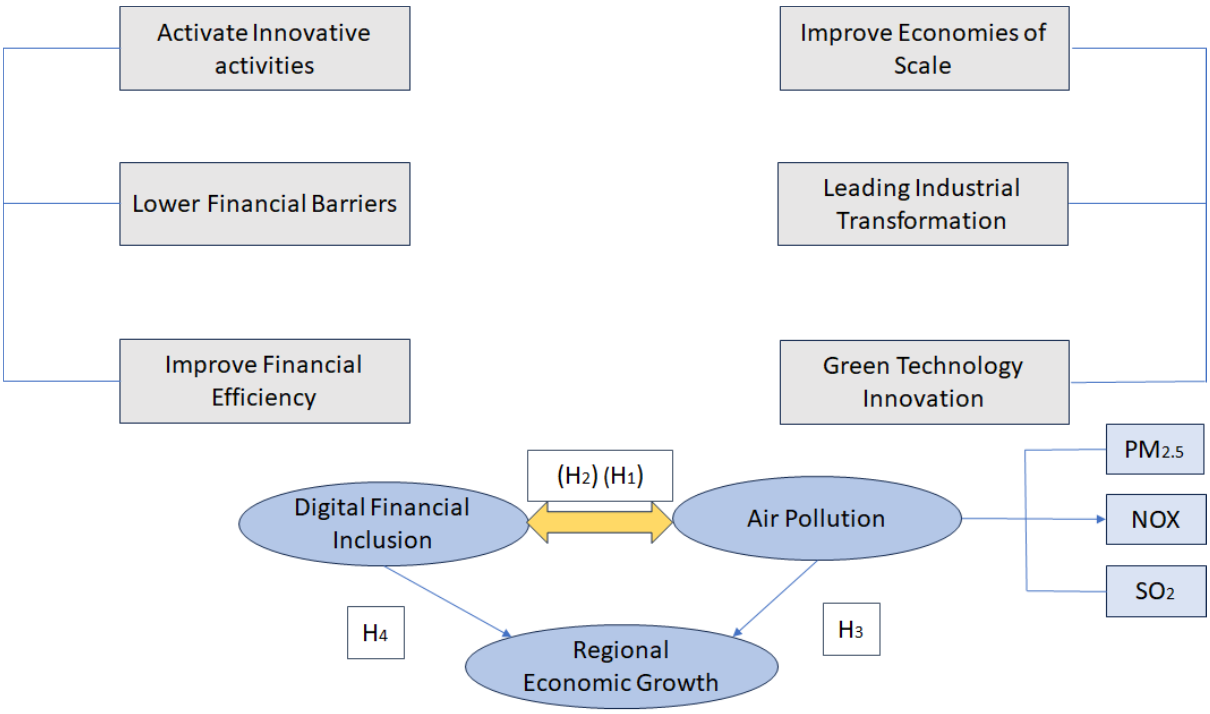

Figure 2. Theoretical framework

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Empirical Methodology

The purpose of this study is to examine the impact of DFII on GRP per province using threshold panel data models. According to Ding *et al.* (2022), our model is presented as follows:

$$lnGRP_{it} = \beta_0 + \beta_1 lnPOP_{it} + \beta_2 lnGFCF_{it} + \beta_3 lnEII_{it} + \beta_4 lnDFII_{it} + \beta_5 lnSO2_{it} + \beta_6 lnNOX_{it} + \beta_7 lnPM2.5_{it} + \lambda_i + \varepsilon_{it} \quad (1)$$

where ε_{it} is the related error term and λ_i is the unobserved effect, representing the individual effect. The subscript $i = 1, \dots, N$ refers to the individual measurement, and the subscript $t = 1, \dots, T$ refers to the time measurement. "ln" refers to natural logarithms. The definition of attributes and the sources are presented in Table 1.

Table 1. Definition of variables

Variable	Designation	Source	References
GRP	Gross Regional Product (100 million Yuan)	NBS	Ding *et al.* (2022), Li *et al.* (2022)
POP	Resident Population (year-end) (10000 persons)	NBS	Kalai *et al.* (2024)
GFCF	Gross Fixed Capital Formation (% of GDP)	NBS	Chen *et al.* (2022), Kalai *et al.* (2024)
EII	Energy Industrial Investment (100 million Yuan)	NBS	Zahoor *et al.* (2022), Li & Li (2020)
DFII	Digital Financial Inclusion Index	PKU-DFII	Ding *et al.* (2022), Ahmad *et al.* (2021), Yang *et al.* (2022)
SO2	Sulphur Dioxide Emission in Waste Gas (10000 tons)	NBS	Zeraibi, Jahanger *et al.* (2023), Lou *et al.* (2021), Ramakrishnan *et al.* (2016)
NOX	Nitrogen Oxide Emission in Waste Gas (10000 tons)	NBS	Ramakrishnan *et al.* (2016)
PM2.5	Atmospheric particulate matter that has a diameter of less than 2.5 µm	TAP Data	Bildirici & Çoban Kayıkçı (2024), Qi *et al.* (2022)

Notes: NBS represents the National Bank Statistics; PKU-DFII indicates the Peking University Digital Finance Institute; and TAP Data represents the Tracking Air Pollution Data.

This study highlights the importance of considering the determinants of the non-linear relationship between digital financial inclusion and regional economic growth across Chinese provinces. By assessing macroeconomic factors (air pollution, capital investment, energy industry, and human capital), we can summarize our approach in Figure 3.

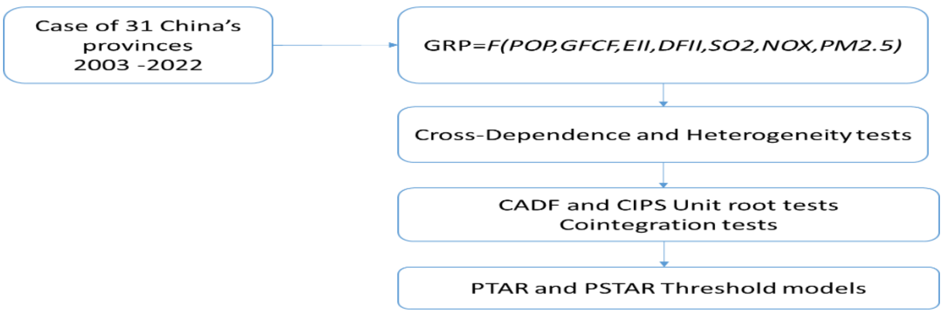

Figure 3. Methodological framework

As the purpose of this research is to detect the existence of structural non-linearity in the GRP-DFII link, we will also seek to determine whether thresholds are characterizing the relationship between DFII and GRP in 31 Chinese provinces between 2003 and 2022. The Panel Threshold Auto-Regressive (PTAR) model was established by Hansen (1999). Using this model, the endogenous variable y_{it} depends on several different non-dynamic relationships. Consequently, the process $y_{it}, t \in Z, i \in Z$ (Equation 1) satisfies a two-regime PTAR model only if:

$$y_{it} = \mu_i + \sum_{j=1}^{p} \rho_j \, y_{\text{it}-\text{j}} + \beta_1' X_{it} + \beta_2' X_{it} I(q_{it} > c) + \varepsilon_{it} \tag{2}$$

where μ_i is the vector of individual fixed coefficients, ρ_j is the autoregressive coefficients of the process y_{it} , $I(q_{it} > c)$ denotes the indicator function concerning the transition variable q_{it} and the threshold parameter c, $X_{it} = (X_{it}^1, \dots, X_{it}^k)$ is the matrix of k exogenous variables that do not contain lagged explanatory variables, $\beta = (\beta_1, \dots, \beta_k)$ and $\varepsilon_{it} \sim N(0, \sigma^2)$.

For their part, González *et al.* (2005) proposed to reinforce the PTAR model by creating a model called PSTAR. The purpose of this model is to move from a fast transition approach to a smooth transition approach in the case of time series. Thus, the process $y_{it}, t \in Z, i \in Z$, conforms to a two-regime PSTAR model (Equation 3) if and only if:

$$y_{it} = \mu_i + \sum_{j=1}^{p} \rho_j \, y_{\text{it}-\text{j}} + \beta_1' X_{it} + \beta_2' X_{it} G(q_{it}; \gamma, c) + \varepsilon_{it} \tag{3}$$

where $G(q_{it}; \gamma, c)$ signifies the transition function for the transition variable q_{it}, the threshold parameter c, and the smoothing coefficient γ.

As a preliminary step, it is crucial to estimate the PSTAR model and check for linearity, specifically the existence of a statistically significant regime-switching effect. González *et al.* (2017) outlined a procedure to test the null hypothesis of linearity ($H_0: {\beta_2}' = 0$, equivalent to $H_0: \gamma = 0$) in the context of a PSTAR model. It is possible to apply the Wald, Fisher, and LR tests, where the corresponding statistics for each (specified in Equation 4) are as follows:

$$LM_w = \frac{TN(RSS_0 - RSS_1)}{RSS_0};\ LM_F = \frac{TN(RSS_0 - RSS_1)/K}{RSS_0/(TN - N - K)};\ LR = -2[log(RSS_0) - log(RSS_1)] \tag{4}$$

where RSS_0 and RSS_1 are the panel residual sum of squares. Under the null hypothesis, the Wald LM_w, LR statistics are calculated according to a chi-squared distribution with K degrees of freedom, representing the number of variables; and the LM_F statistics follow a chi-squared distribution.

Empirical Results

In what follows, we show the relative descriptive statistics of the different variables changed into a logarithm (see Table 2). By using the Jarque & Bera (1987) normality test and the Born & Breitung (2016) serial autocorrelation test, the null hypothesis of these two tests is rejected.

Table 2. Retrieval of the various descriptive statistics of the series

	GRP	POP	EII	GFCF	DFII	SO2	NOX	PM2.5
Observation	620	620	620	620	620	620	620	620
Mean	9.29	8.10	6.23	8.88	4.56	3.27	3.81	3.63
Median	9.42	8.24	6.38	8.98	4.84	3.70	3.91	3.62
SD	1.19	0.85	0.98	1.23	1.06	1.54	0.89	0.46
Min	5.22	5.60	2.30	4.89	2.43	-2.31	1.22	2.14
Maxi	11.76	9.44	8.22	11.05	5.98	5.29	5.21	4.72
Skewness	-0.62	-0.97	-0.80	-0.53	-0.27	-1.42	-0.83	0.09
Kurtosis	3.33	3.52	4.00	2.92	1.54	4.95	3.43	2.54
JB test	43.06	105.60	93.91	29.48	62.74	307.30	76.09	6.34
JB Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
BB test	983.86	18.32	141.98	327.97	305.73	105.34	108.57	106.64
BB Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: JB refers to the Jarque & Bera (1987) normality test. BB refers to Born & Breitung (2016). SD represents the standard deviation. All variables are in natural logs.

The "LnGRP" variable shows an overall mean of 9.292 with a standard deviation of 1.192. The form of the supply is extended to the left because the skewness statistic equals -0.623 < 0. All values are bounded between 5.225 and 11.768, with a strong concentration around 9.429.

For the "LnDFII" variable, the series has an average of 4.568 with a large standard deviation of 1.068. The 620 observations ranged between 2.431 and 5.984, with a strong concentration around 4.849. The distribution is asymmetric spread on the left since the skewness is equal to -0.275, and once again it is leptokurtic, where the kurtosis = 1.542 > 0.

Following globalization, cross-sectional dependence may be within and among nations as well as regional economies (De Hoyos & Sarafidis, 2006; Bilgili *et al.*, 2017; Dong *et al.*, 2018; Shahbaz *et al.*, 2018). In addition, the unit root and panel cointegration tests are greatly skewed if the cross-sectional dependence is not taken into account (O'Connell, 1998; Atasoy, 2017; Pesaran, 2021).

Table 3. Cross-dependence and heterogeneity tests

Tests	Value	Probability	Decision
Friedman (1937)	220.054	0.000	Dependence
Breusch & Pagan (1980)	1666	0.000	Dependence
Frees (1995); (2004)	6.492	0.000	Dependence
Pesaran (2004)	35.74	0.000	Dependence
Pesaran (2006)	34.631	0.000	Dependence
Pesaran *et al.* (2008)	53.97	0.000	Dependence
Pesaran (2015)	25.335	0.000	Dependence
Pesaran & Yamagata (2008)	11.372 15.334	0.000 0.000	Heterogeneity

Therefore, the tests suggested by Friedman (1937), Breusch & Pagan (1980), Frees (1995), Pesaran (2004), Pesaran (2006), Peseran (2015), and Pesaran *et al.* (2008) are used to test cross-sectional dependence. These tests were crucial in identifying how frequently shocks occurred in the cross-sectional portion of the data set. Regarding Table 3, the result indicates a breakdown to reject the cross-sectional independent null hypothesis. In addition, the second

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panel in Table 3 tests the hypothesis of homogeneity proposed by Pesaran & Yamagata (2008). The results of the homogeneity test reveal that the two statistics indicate statistically significant probability values at the 1% level, leading us to accept the alternative hypothesis of heterogeneous coefficients.

Due to the presence of cross-sectional dependency and heterogeneity, we employ Pesaran (2003) and Pesaran (2007) second-generation unit root tests. Table 4 shows that all series show the presence of unit roots in level (rejection H0). As a result, we can assume that all of the series are integrated into order 1. As a result, we must investigate the cointegration relationship between variables using the first-generation tests of Kao (1999), Pedroni (2004), and Westerlund (2007), as well as a second-generation test of Persyn & Westerlund (2008). See Table 5.

Table 4. Results of the second generation of unit root test

	GRP	POP	GFCF	EII	DFII	SO2	NOX	PM2.5
Pesaran (2003)								
				Panel A: In level				
C	-2.19***	-2.20***	-2.94***	-2.03*	-2.67***	-2.27***	-1.66	-2.75***
C & T	-2.16	-1.64	-2.73***	-2.70**	-2.77***	-2.89***	-1.98	-3.18***
Decision	NS	NS	S	S	S	S	NS	S
				Panel B: In first difference				
C	-2.38***	-1.89	-2.71***	-3.15***	-3.20***	-3.25***	-2.64***	-3.66***
C & T	-2.66**	-2.31	-2.86***	-3.10***	-3.26***	-3.65***	-3.45***	-3.68***
Decision	S	NS	S	S	S	S	S	S
Pesaran (2007)								
				Panel A: In level				
C	-2.02	-2.04	-2.83***	-2.35***	-4.35***	-2.40***	-1.52	-2.90***
C & T	-2.16	-0.99	-2.42	-2.98***	-4.39***	-3.23***	-2.25	-3.28***
Decision	NS	NS	NS	S	S	S	S	S
				Panel B: In first difference				
C	-3.29***	-2.65***	-3.36***	-4.08***	-5.19***	-4.35***	-2.85***	-4.55***
C & T	-3.48***	-3.24***	-3.52***	-4.11***	-5.28***	-4.88***	-3.48***	-4.49***
Decision	S	S	S	S	S	S	S	S

Notes: ***, **, * represent the significance at 1%, 5%, and 10%; C: Constant; T: Trend; NS: Non-Stationary; S: Stationary; All variables are in natural logs.

Table 5. Results of cointegration tests

	Tests	Value		p-value		Decision
First generation	Kao (1999)	-2.895		0.00		Cointegration
	Pedroni (2004)	-4.192		0.00		Cointegration
	Westerlund (2007)	-2.012		0.02		Cointegration
Second generation	**Persyn & Westerlund (2008)**	**Value**	**Z-value**	**p-value**	**Robust p-value**	**Decision**
	G_t	-4.29	-5.98	0.00	0.00	Cointegration
	G_a	-5.07	3.22	0.99	0.00	Cointegration
	P_t	-18.96	-8.23	0.00	0.00	Cointegration
	P_a	-6.73	0.24	0.59	0.01	Cointegration

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Table 6. Test for the presence of LNDFII threshold effects in the PTAR model

Hypothesis	Threshold	F-test	p-value	Confidence Interval	RSS	Residual variance
H_0: No threshold	4.264	85.279	0.000	[4.239–4.292]	1.585	0.002

Notes: Test the null of no threshold against the alternative of one threshold. The threshold is obtained by minimizing the residual sum of squares (RSS).

The next step consists of estimating our model using the PTAR and PSTAR approaches. We obtained the number of Lags equal to "1" (either $\chi^2(2) = 1280.94$), which means both models can be performed in Lag 1. We move to use the PTAR(1) model. Therefore, we begin by testing the linearity hypothesis on the link between LnDFII and LnGRP variables. Using the 1000 bootstrap procedure, the results of Table 6 show that the null hypothesis of no threshold is rejected at the 1% level, and there is one threshold obtained equal to LnDFII = 4.264 (i.e., DFII = 71.094).

Our focus will shift towards examining the correlation between the DFII and the GRP within the varying LnDFII systems listed in Table 7. During the initial phase (LnDFII ≤ 4.264), there is a significant impact at the 5% level, so this result has a favourable impact on economic growth. The magnitude and direction of the DFII coefficient are dependent on the level of DFII in this low-LnDFII area, where the elasticity of DFII on economic growth is notably positive (0.061). A 1% rise in DFII leads to a 0.061% surge in regional economic growth, which further results in a 0.049% reduction in $PM_{2.5}$ emissions. The empirical and theoretical research (Cao *et al.*, 2021; Ding *et al.*, 2022) supports the estimated nonlinear relationship between digital financial inclusion and economic growth. This indicates that economic growth is stimulated when DFII falls below a particular threshold.

Table 7. PTAR(1) regression output

Variables	Regime 1: $LnDFII_{it-1} \le 4.264$		Regime 2: $LnDFII_{it-1} > 4.264$	
	Coefficient	t-statistic	Coefficient	t-statistic
$LnGRP_{it-1}$	0.731	21.465***	0.859	32.615***
$LnPOP_{it}$	0.092	1.429	0.105	1.370
$LnGFCF_{it}$	0.160	6.867***	0.019	1.405
$LnEII_{it}$	-0.040	-3.608***	0.005	2.608***
$LnDFII_{it}$	0.061	3.475***	0.015	2.296**
$LnSO_{2it}$	0.008	0.953	-0.004	-2.651***
$LnNOX_{it}$	0.014	0.601	-0.043	-2.322**
$LnPM_{2.5it}$	-0.049	-2.186**	-0.030	-2.478**

Note: *** and ** show the significance at 1% and 5% levels, respectively.

In the second regime (LnDFII > 4.264), its slight growth-enhancing effect is quite positive (0.015%). Due to this increase, the reduction of SO_2, NOX, and $PM_{2.5}$ has a positive impact on GRP. Statistically, this discount boosts economic growth by 0.004%, 0.043%, and 0.030%, respectively.

The PTAR model may struggle with accurately identifying and estimating threshold values, leading to potential misspecification issues, while the PSTAR model alleviates this concern by allowing for continuous transition functions. For this reason, we move on to estimate the PSTAR model.

We start by carrying out the linearity test, which allows us to define the number of thresholds. Table 8 displays the results of the Wald LM_w test, Fisher LM_F test, and LR test. The p-values show that there is a single threshold with a 1% probability for a logistic PSTAR model (m = 1). This implies that the DFII-GRP relationship is non-linear.

Table 8. PSTAR(1) linearity tests

	H0: r=0 vs H1: r=1		H0: r=1 vs H1: r=2	
Tests	**t-Statistic**	**Probability**	**t-Statistic**	**Probability**
Wald (LM_w)	70.565	0.000	5.807	0.098
Fisher (LM_F)	9.327	0.000	1.067	0.092
Likelihood Ratio (LR)	74.914	0.000	6.360	0.111

Table 9. Test for the existence of DFII threshold effects

Order	Threshold ($\hat{c}$)	Parameter of transition ($\hat{\gamma}$)	RSS	AIC	BIC
m=1; r=1	4.563	4.816	1.465	-5.890	-5.761

The results of Table 9 suggest that the estimated threshold is equal to 4.563 and the transition parameter γ is equal to 4.816. In addition, the minimum values of RSS, AIC, and BIC are touched for values equal to 1.465, -5.890, and -5.761, respectively.

For the PSTAR model, the results indicate the existence of two separate regimes. As shown in Table 10, the threshold value for the LnDFII variable is equal to 4.563. Statistically, the first regime shows that the variables LnPOP, LnGFCF, and LnDFII have a positive and significant impact on the variable LnGRP, with elasticities of 0.14, 0.158, and 0.063, respectively. However, both LnEII and $LnPM_{2.5}$ have a negative and significant effect on the variable LnGRP, with elasticities of -0.03 and -0.043, respectively. For the second regime, all the variables have a significant effect on LnGRP, while the variable LnPOP does not have a significant effect. The variables LnGFCF, LnEII, LnDFII, and LnNOX have a positive effect of 0.127, 0.025, 0.004, and 0.037, respectively, while the variables $LnSO_2$ and $LnPM_{2.5}$ have a slightly negative effect.

The DFII can help small enterprises and people living in rural areas by easing their financial constraints. For provinces linked to the economy, digital financial inclusion can create spillover effects in terms of technological innovation and the inter-regional economy, encouraging the continued improvement of the industrial structure. These developments stimulate economic development in other regions through the flow of factors of production (Liu *et al.*, 2023).

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Table 10. PSTAR(1) regression

Variables	Regime 1: $LnDFII_{it-1} \leq 4.563$		Regime 2: $LnDFII_{it-1} > 4.563$	
	Coefficient	t-statistic	Coefficient	t-statistic
$LnGRP_{it-1}$	0.720	22.303***	0.105	3.965***
$LnPOP_{it}$	0.140	2.063**	0.006	0.310
$LnGFCF_{it}$	0.158	7.123***	0.127	5.946***
$LnEII_{it}$	-0.030	-2.658***	0.025	1.980**
$LnDFII_{it}$	0.063	4.231***	0.004	2.280**
$LnSO2_{it}$	-0.0002	-0.028	-0.006	-2.629***
$LnNOX_{it}$	-0.004	-0.212	0.037	-1.922**
$LnPM2.5_{it}$	-0.043	-1.835**	-0.001	-2.132**

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

In China, digital financial inclusion promoted through platforms has played a crucial role in promoting financial prosperity. These mobile payment solutions transform transactions by enabling electronic payments through smartphones, reducing dependence on cash, and increasing financial efficiency. Furthermore, digital financial inclusion can help reduce pollution in China by promoting a shift toward more sustainable and environmentally friendly business and industrial practices. It can encourage investment in clean technologies and green business practices by providing wider access to financial services, especially to rural populations and small businesses.

Due to the development of the digital economy, concentrations of $PM_{2.5}$, industrial wastewater discharges, and industrial emissions of sulphur dioxide, soot, and dust have fallen significantly. Moreover, the constructive effects of the digital economy on the decline of environmental pollution are more pronounced in central and western China. Hypotheses (**H2**) and (**H3**) have therefore been validated based on these data.

Moreover, the primary method by which the digital economy reduces pollutant emissions is through the promotion of industrial restructuring and advances in eco-friendly technology. Furthermore, the digital economy's ability to reduce pollution depends on the threshold level of economic development. As a result, conjecture (**H1**) has been confirmed. Further analysis of this threshold effect reveals that the more developed an economy is, the greater the reduction in emissions will be (Guo *et al.*, 2023).

The transition function is defined as a mathematical function that determines how the relationship between two variables changes when a threshold variable exceeds a certain threshold value. Thus, and regarding Figure 4, the estimated value of the smoothing parameter, equal to $\hat{\gamma}$ = 4.816, is assumed to be low and suggests that the switch of transition from the first regime to the second is smooth.

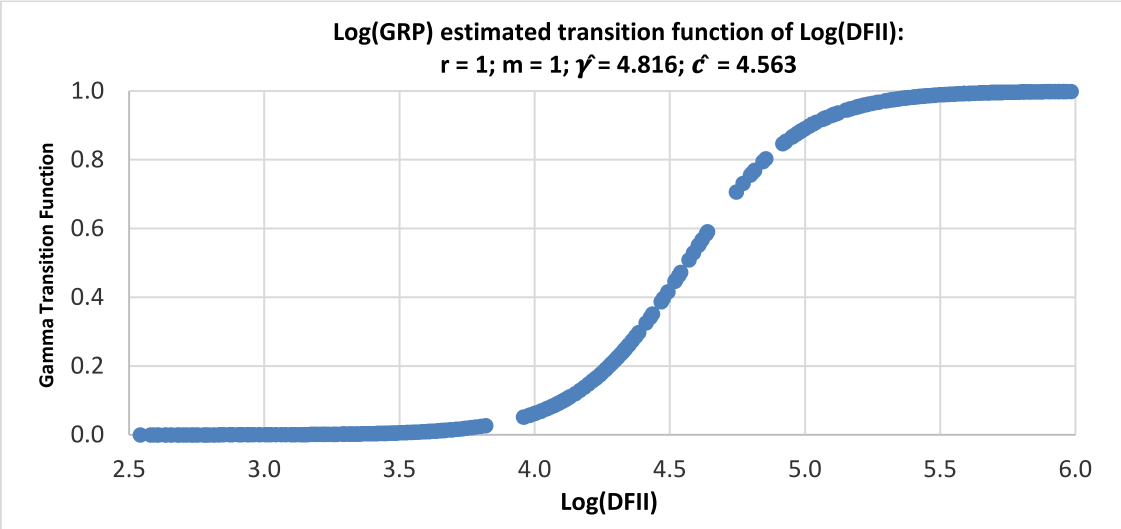

Figure 4. Log (GRP) estimated transition function of Log (DFII)

Consequently, it is possible to conclude that the LnDFII variable and LnGRP support the idea of a non-linear association. However, when digital financial inclusion increases beyond this threshold value, the relationship between the two variables becomes much stronger.

After constructing the PSTAR model, we can conclude that digital finance has a positive impact on the level of air pollution and economic growth. Moreover, the findings confirm the non-linearity between DFII and GRP in China's provinces. As a result, hypothesis ($\mathbf{H_4}$) is supported.

Conclusion and Policy Implications

For China, the creation of a digital economy is essential to achieving high-quality development, and the digital financial sector is an excellent tool for a new financial development model that is of considerable importance. To examine the impact of digital financial inclusion and air pollution on economic growth, this study uses provincial panel data from 2003 to 2022 and conducts empirical analysis based on existing theory and literature. According to the results, there are two thresholds for digital financial inclusion, with respective values of 4.264 for the PTAR model and 4.563 for the PSTAR model, and both regimes have a positive and significant marginal impact on regional growth. However, the impact is weaker in the second regime. Furthermore, the PTAR and PSTAR models demonstrate that reducing air pollution through digital financial inclusion has a crucial effect on regional economic growth.

In terms of digital financial inclusion, the following policy recommendations aim to facilitate access to financial services through digital channels. Firstly, governments need to strengthen the overall infrastructure for the digital financial system to ensure inclusiveness, put in place a sound organizational management framework, and increase the performance and effectiveness of digital finance in supporting the real economy. Secondly, to foster the positive impact of digital financial inclusion on economic growth, it is imperative for the authorities to judiciously implement digital technologies and bolster regional collaboration.

Therefore, to encourage financial institutions to expand their digital financial services and reduce transaction costs in underdeveloped areas, public authorities should provide financial support and develop infrastructure. In addition, financial institutions should introduce innovative financial services into the developed regions of the East to encourage local economic growth and innovation. Fourthly, financial regulators should utilize digital technology to learn from advanced experiences and expedite the establishment of regulatory guidelines for the inclusive digital financial sector. This will increase the flexibility, inventiveness, and effectiveness of supervision.

Moreover, the argument assumes that digital financial inclusion can represent a fundamental cause, namely financial prosperity (Zhao & Jiao, 2024). Indeed, where an increase in financial prosperity is related to an increase in digital financial inclusion, a reduction progressively in environmental pollution follows. Therefore, conclusions in favour of promoting digital financial inclusion as a pollution control measure are considered untenable. By addressing the root causes of financial wellbeing, policymakers have the potential to achieve dual benefits: improving digital financial inclusion and reducing pollution. Therefore, the focus should shift from promoting digital financial inclusion alone to implementing measures that comprehensively improve overall financial wellbeing, thereby indirectly addressing environmental issues.

There were limitations to this research, which should be taken into account in other studies. There are some limitations in using PTAR (panel threshold autoregressive) and PSTAR (panel smooth transition autoregression) models to examine the impact of digital financial inclusion on regional economic growth in China. First, while these models allow for non-linear relationships and threshold effects, they may require specifying threshold levels *a priori*, which can be difficult and subjective. Furthermore, using combined regional data in panel models might not take into account differences within regions and hide important differences in how digital financial inclusion affects economic growth in various regions.

In addition, the connection between digital financial inclusion and environmental pollution has its limitations. While digital financial inclusion has the potential to reduce pollution by financing green initiatives, comprehensive data on the scale and effectiveness of such initiatives may be lacking, making it difficult to accurately quantify their impact. Furthermore, it can be hard to determine what causes what when it comes to digital financial inclusion and environmental effects. This is because of the long-term nature of environmental changes and the presence of confounding factors. To solve these problems, we need strong methods and data sources.

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