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Editorial Team

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Editorial

Australia's National Artificial Intelligence Plan

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Abstract: As with many countries in the world that are primarily technology takers, rather than technology leaders, Australia is seeking to address the issues for its place in the global digital ecosystem and to identify, and then realise, the opportunities that artificial intelligence (AI) may bring. On 2 December 2025, the Australian Government published its much-awaited National Artificial Intelligence Plan. In our editorial, we broadly summarise the Plan and discuss some initial reactions to it. We hope to revisit the subject in 2026 to find out how the Plan has fared at that stage. Also, we outline the eight technical papers published in this issue. In personnel changes, we note the resignation of the previous Editor-in-Chief.

Keywords: Editorial, AI, Artificial Intelligence, National Plans, Australian Government

Australia's *National Artificial Intelligence Plan* – Is Excitement Premature?

On 2 December 2025, the Minister for Industry and Innovation and the Assistant Minister for Science, Technology and the Digital Economy jointly launched the Commonwealth Government's National Artificial Intelligence (AI) Plan – hereafter the Plan (Industry, 2025).

In a nutshell, the Plan is, in the words of the Ministers:

> "… a key pillar of the government's Future Made in Australia agenda. By building sovereign capability in AI, supporting local innovation and ensuring that Australian workers and businesses are equipped to lead in the global digital economy, we are laying the foundations for a more resilient and competitive Australia. The National AI Plan complements our broader efforts to revitalise Australian industry, create high-value jobs and ensure that the benefits of technological progress are realised here at home" (Industry, 2025, p. 5).

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The Plan has three goals: (1) capturing the AI opportunity; (2) spreading the AI benefits; and (3) keeping Australians safe. The Plan proposes to capture the AI opportunity by building smart infrastructure (with much emphasis on data centres), by backing Australian AI capability, and by attracting investment to the Australian AI sector. Building smart infrastructure involves considerably more than facilitating data centre development. The Plan includes expanding the National Broadband Network, investing in cybersecurity and securing critical infrastructure, and guiding future investing to and within the AI sector.

The Government's National AI Centre (NAIC, 2024), established in 2021 has an important role in supporting industry to unlock the economic benefits of AI and in developing widespread AI literacy in industry and the workforce generally. The Plan reinforces that role.

The AI ecosystem involves a wide diversity of organisations and institutions. The roles of these are noted in the Plan, from Cooperative Research Centres, to a myriad of different ministries, educational, employers, trade unions, urban planning and utility authorities (in relation to data centres), and many others. In addition to the NAIC, the Plan includes the establishment an AI Safety Institute (AISI) to monitor, test and share information on emerging AI capabilities, risks and harms.

Then, there is the matter of money. The Plan does not propose any new Government money to fund its AI ambitions. However, it does note that "the government is backing this ambition with more than $460 million in existing funding already available or committed to AI and related initiatives" (Industry, 2025, p. 13). The $460 million is made up of:

- over $362 million in targeted grants from the Australian Research Council, Medical Research Future Fund, National Health and Medical Research Council, and Cooperative Research Centres;
- $47 million for the Next Generation Graduates Program;
- $39.9 million to strengthen Australia's AI ecosystem, which includes expanding the NAIC; and
- $17 million for the AI Adopt Program to support SMEs.

So, how has the Plan been received? Overall, without enthusiasm. It received no coverage in some industry media, and elicited scepticism in others.

For example, James Riley, the Editorial Director of InnovationAus.com accused the Plan of not being a plan at all and of lacking ambition. He wrote: "… it delivers a set of blue-sky aspirations or objectives, but without describing the steps to reach those objectives. Without detail or focus, this is a plan that smells a lot like wishful thinking" (Riley, 2025). He further notes that "there is no ambition for building Australia's AI talent pipeline with the best and brightest". That ambition would have required significant new funding.

TelSoc, the publisher of this *Journal*, has for many years advocated Government leadership in developing meaningful plans to secure Australia's digital future. TelSoc's interest to date has been in terms of broadband and related infrastructure, rather than AI specifically (TelSoc, 2021). The publication of a Plan of this kind meets some of TelSoc's aims, including that the Government should take a leadership and coordinating role, rather than rely unduly on the market to shape outcomes. Perhaps the Plan might be best regarded as the start of a coordinated public conversation on Australia's AI future and priorities, rather than as a comprehensive blueprint to achieve goals by, say, 2030 or 2035. The actual goals in the Plan for 2030 are vague in any case. For example, under Capturing the Opportunities: "By 2030 … [o]ur digital infrastructure sustainably supports AI innovation to benefit our communities" (Industry, 2025, p. 9). Perhaps they will become specific and measurable as the Plan is revised and reviewed.

The Plan has been a while in the making and satisfies the Australian Government's immediate political requirement to have a reasonably compelling document that it can point to as its plan for AI. But is the Plan more than a performative exercise, or does it provide a substantive boost to the development of a commercially viable, ethically acceptable AI industry in Australia? Clearly, it is too early to tell, but the question should be asked time and again as we move into this new era. We have seen many fine statements, plans and reports published with fanfare over the past decade, only to wither on the vine through neglect and lack of commitment to follow through. That is a risk with this Plan, but perhaps the noise levels and daily reinforcement of the importance of AI will ensure this Plan becomes something more.

In This Issue

Continuing the theme of AI, this issue includes two papers that principally depend on AI techniques. Purwanto *et al.* (2025), published in the section on Digital Economy & Society, describe an AI-based model for predicting sales in small and medium enterprises, supporting their digital transformation. Kahoul *et al.* (2025) in the Telecommunications section demonstrate, using real operational data from Algeria, how an ensemble of AI techniques, including explainable AI, can be used for identifying anomalies in LTE networks. We receive many submissions on the use of AI and expect to publish many more in the future.

In the Digital Economy & Society section, in addition to Purwanto *et al.* (2025), there is one other paper. Mgadmi *et al.* (2025) look at the effects that financial technologies have on economic growth and foreign direct investments, using data from both developed and developing economies.

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In the Telecommunications section, we have three papers, including Kahoul *et al.* (2025) described earlier. Balcioğlu *et al.* (2025) look at how paid subscriptions affect the way users engage with social media platforms, with data from Instagram. Agrawal & Sridhar (2025) consider how to continue public Wi-Fi programs through regulatory support.

We include two Industry Case Studies. The first, by Ramirez *et al.* (2025), describes a process mining technique to identify bottlenecks and other adverse features in customer-facing operations. Hentati & Jallouli (2025) undertake a systematic literature review to summarize how text-mining methods are being used in mobile banking apps to assess user satisfaction.

This issue's historical reprint (Moorhead, 2025) continues our interest in the state of broadband services in Australia with a look back to a tutorial paper on the situation in 2007.

As always, we welcome comments from our readers on any of these topics.

Personnel Changes

Dr Michael de Percy resigned as Editor-in-Chief in October due to changed personal circumstances. He remains a member of the Board of Editors and an Associate Editor for Public Policy. We thank Michael de Percy for successfully stewarding the first three issues of 2025.

The TelSoc Board has appointed Dr Leith Campbell, a former Managing Editor, as the new Editor-in-Chief, with Dr Jim Holmes as his Deputy. This is an interim arrangement until a longer-term Editor-in-Chief can be found.

We welcome Dr Aviv Yuniar Rahman from Universitas Widyagama in Indonesia as the new Associate Editor for Industry Case Studies.

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Fin-Tech Moderator Role in Attracting Foreign Direct Investments and Economic Growth

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Abstract: This study examines the moderating role of financial technology (Fin-Tech) in the attractiveness of foreign direct investment (FDI) and its impact in stimulating economic growth, with a particular focus on financial inclusion. The results reveal that in developed countries, various macroeconomic, institutional and Fin-Tech-related indicators have positive and statistically significant impacts on economic growth. Additionally, the quality of regulations and political stability are crucial determinants of FDI attractiveness in these countries. In contrast, variables such as interest rates and economic growth, measured by gross domestic product (GDP), do not demonstrate a significant contribution to FDI attractiveness. Furthermore, Fin-Tech technologies, such as digital payments and peer-to-peer lending (PPL), enhance FDI attractiveness, particularly when accompanied by robust institutional regulations and political stability. However, this effect diminishes in the presence of corruption controls. In developing countries, while most macroeconomic indicators have a positive influence on economic growth, the balance of payment deficit remains an outlier. The quality of regulation and use of digital payments also play significant roles, while PPL appears to have a negative effect. Finally, FDI in developing countries is more strongly influenced by factors such as population growth and institutional quality, especially regulatory quality and political stability.

Keywords: Attractiveness of FDI, GDP, Fin-Tech, economic growth

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Introduction

Foreign direct investment (FDI) plays a crucial role in fostering economic growth by providing capital, technology and employment opportunities in host countries (Ju *et al.*, 2023). The International Monetary Fund (IMF) enhances productivity and competitiveness by introducing new business models and innovations that can boost the output of national economies (Moosa & Merza, 2022). However, the COVID-19 pandemic has significantly affected global economic growth and investment flows. The COVID-19 pandemic caused a sharp decline in global FDI, as uncertainty and apprehension led to travel restrictions and disruptions for businesses, and slow economic recovery prompted companies to delay or scale back their investment decisions. In addition, this pandemic presented new challenges to the global economy, forcing several sectors into economic contraction (Moosa & Merza, 2022).

The investment climate deteriorated due to declining GDP in many countries as the COVID-19 pandemic created widespread economic disruption. Simultaneously, this pandemic fuelled interest in financial technology (Fin-Tech) services, which enabled users to conduct financial transactions online and via mobile devices. This shift was driven by not only the accelerated adoption of digital technologies but also by the diminishing viability of traditional investment channels, as noted in the United Nations Conference's *World Investment Report* (United Nations Conference on Trade and Development, 2021). Fin-Tech emerged as a viable solution, offering innovative financial services and processes tailored to the evolving needs of consumers and businesses, particularly during the lockdowns (Zheng & Li, 2022).

The global economy contracted by 3% (Long & Ascent, 2020) at the peak of the COVID-19 pandemic, according to estimates from the IMF, in June 2020. As a result, other institutions involved in economic forecasting had to revise their expectations for both global and national growth in 2020, as detailed in the IMF's report on policy responses to COVID-19 (IMF, 2020). Consequently, the rapid rise in Fin-Tech during the pandemic rendered investments in the sector particularly attractive. With businesses forced to adopt work-from-home practices, Fin-Tech firms proved resilient, designing services such as digital payments, online lending and investment platforms in ways that enable users to access them remotely, without physical contact. This shift not only attracted local investments, but also drew foreign investors to emerging markets (Hysa *et al.*, 2022).

By expanding the overall investment environment through new channels for capital allocation, Fin-Tech growth has significant implications for FDI and economic development in both developed and developing countries (Hysa *et al.*, 2022). FDI has long been a key driver of economic growth, but the COVID-19 pandemic has altered the landscape, shifting traditional business models and rendering Fin-Tech a critical alternative for economic recovery. In this context, Fin-Tech plays a central role in revitalising economies from various perspectives (World Bank, 2022). It disrupts traditional financial services by offering innovative solutions that drive efficiency, accessibility, and transparency to an unprecedented degree. As economies face challenges related to development and the need to attract FDI, the importance of Fin-Tech has grown significantly (Bhattacharjee *et al.*, 2024).

This study explores the influence of Fin-Tech on economic growth and its capacity to attract foreign capital, particularly in developing markets, by promoting financial inclusion, lowering transaction costs and supporting entrepreneurial ecosystems. In this way, Fin-Tech not only stimulates local economies, but also enhances the appeal of countries to foreign investors seeking new opportunities (Abzari *et al.*, 2011). Moreover, the integration of advanced technologies, such as blockchain and artificial intelligence, within the Fin-Tech sector is improving the overall investment climate, offering investors greater returns and lower risks (Wang & Chen, 2024). Our study aims to examine the effects of Fin-Tech on economic growth and FDI through a comparative analysis of developed and developing countries, emphasising institutional differences and the specific challenges faced by developed and developing countries. While extensive research has examined the broader impact of FDI on economic growth, a significant gap remains in understanding how Fin-Tech advancements influence these dynamics. This study seeks to bridge that gap by analysing the complex relationships between Fin-Tech development, national economic growth and the attraction of foreign investment, with a particular focus on comparing developing countries to a sample of developed nations.

Our article makes important contributions to the literature on Fin-Tech, FDI and economic growth by offering a comparative institutional analysis between 36 developed and 33 developing countries. It demonstrates that Fin-Tech, particularly digital payments and peer-to-peer lending (PPL), enhances FDI and economic growth in developed economies when supported by strong institutions such as regulatory quality and political stability. Conversely, in developing countries, while digital payments are beneficial, PPL tends to hinder growth due to weak infrastructure and regulatory gaps. This study also uncovers the nuanced role of institutions, revealing that regulatory quality and political stability amplify Fin-Tech's impact, while corruption control has a limited effect on FDI in developed economies – challenging conventional expectations.

Methodologically, this study employs a robust static panel model with data from 2014 to 2023, capturing recent Fin-Tech developments and the post-COVID-19 landscape. It integrates endogenous growth theory with institutional economics, demonstrating that Fin-Tech fosters growth both directly and through institutional mediation. The findings offer strong policy implications: developing countries should prioritise digital infrastructure and regulatory frameworks, whereas developed nations should enhance political stability to harness Fin-Tech's full potential. Moreover, this article highlights that FDI is not solely driven by growth, but more critically by institutional quality and Fin-Tech integration, offering valuable insights for sustainable development strategies.

This article is organised into three key parts. The first section provides a comprehensive review of the empirical literature, examining both the positive and negative impacts of Fin-Tech on economic growth and FDI. It highlights how Fin-Tech fosters financial inclusion, reduces transaction costs and enhances investment efficiency in developed and developing countries. It also addresses potential challenges, such as regulatory gaps, data security risks and unequal access to digital financial services. The literature review emphasises the contrasting effects of Fin-Tech, shaped by varying economic structures, governance frameworks and technological readiness in different countries. The second section focuses on empirical analysis by employing a static panel model to compare the influence of Fin-Tech on economic growth and FDI in developed and developing countries. This section details the methodology, data sources and variables that were used to ensure a robust comparative framework. The analysis delves into the role of key factors such as regulatory quality, political stability, corruption and infrastructural capacity in shaping the relationship between Fin-Tech, economic growth and FDI. The final section presents a discussion of empirical findings and offers insights into how Fin-Tech contributes to economic growth and FDI under varying economic and institutional conditions. It outlines policy recommendations for maximising the potential of Fin-Tech, such as strengthening regulatory frameworks, investing in digital infrastructure and promoting financial literacy. This section also identifies the limitations of this study, including data constraints and methodological assumptions, and suggests avenues for future research. These include exploring the dynamic effects of Fin-Tech over time, analysing its impact at the sectoral level and investigating its role in mitigating economic inequalities.

Literature Review

Fin-Tech has revolutionised global financial systems, reducing transaction costs, increasing market efficiency and enhancing transparency (Arner *et al.*, 2020). It is particularly influential in developing economies where traditional financial systems are underdeveloped. In developed economies, Fin-Tech facilitates innovation and economic growth by enhancing the competitiveness of businesses and integrating global financial markets (Zhang *et al.*, 2022). Despite these advantages, the impact of Fin-Tech in developing countries is heavily influenced by the quality of digital infrastructure and the presence of corruption (Abdullahi & Ajulo, 2024). Fin-Tech plays a key role in the attractiveness of FDI by improving the efficiency of financial transactions and market transparency, which enhances the appeal of countries to international investors (Arner *et al.*, 2016; 2020). Its impact on economic growth is particularly pronounced in developed countries, where favourable institutional environments and investments in research and development support innovation and integration of these technologies into economic systems (Zohar, 2019). In contrast, in developing countries, Fin-Tech helps to bridge institutional gaps by offering alternative solutions to overcome economic challenges, but its effectiveness strongly depends on the quality of regulations and efforts to combat corruption, factors that condition its impact in these contexts (Kshetri, 2021).

The existing literature on the impact of Fin-Tech on economic growth and FDI identifies two key effects. Research by Chemmanur *et al.* (2020), Liu & Chu (2024), Mhlanga (2024) and Mitra & Karathanasopoulos (2020) suggested that Fin-Tech can be a significant driver of economic growth. However, the impact of Fin-Tech on growth is not uniform across all Fin-Tech solutions. Cevik (2024) and Sharmin Rahman (2024) further highlighted that while Fin-Tech lending improves financial access, its benefits are often unevenly distributed, particularly in regions constrained by energy shortages that limit growth opportunities. This underscores the need for integrated policies addressing both financial and energy access to foster sustainable development. Despite this expanding body of research, important gaps remain. Notably, there is a lack of empirical data on the long-term effects of Fin-Tech on FDI. Additionally, much of the existing research has focused on developed countries, with limited attention given to developing economies and the varying rates of Fin-Tech adoption across different sectors.

The literature indicates that Fin-Tech has a significant impact on FDI by improving transaction efficiency and increasing access to capital. However, regulatory challenges and regional disparities remain as critical issues that warrant further investigation. Future research should focus on longitudinal data and a broader geographic scope to provide deeper insight into these dynamics. For instance, Loo (2019), Shkurat (2023) and Xu *et al.* (2025) emphasised how inclusive digital finance can promote trade and investment. However, scholars such as Aziz & Wahid (2019) pointed out a notable gap in the literature regarding the potential risks of missing key opportunities for growth and innovation in this rapidly evolving field. Zheng & Li (2022) argued that stringent regulatory frameworks could hinder Fin-Tech adoption, thus limiting potential investment in Fin-Tech. Additionally, Lee & Shin (2018) debated whether Fin-Tech enhances or undermines investor confidence, suggesting that while it may increase transparency, the emerging nature of some technologies could introduce new risks, potentially deterring investment.

The rise of Fin-Tech has profoundly transformed the financial services sector, playing a key role in driving economic growth. As highlighted by Boratynska (2019) and Chemmanur *et al.* (2020), Fin-Tech has not only streamlined financial processes but has also introduced innovative business models that reduce transaction costs and facilitate market access by

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lowering entry barriers. These advancements have improved operational efficiency, strengthened financial inclusion and fostered the emergence of competitive and dynamic economic ecosystems. Mitra & Karathanasopoulos (2020) emphasised that the integration of Fin-Tech solutions into the financial system has driven growth by improving financial accessibility and efficiency. This transformation is particularly evident in developing countries, where Fin-Tech-leveraging mobile technologies has facilitated financial inclusion for marginalised populations (Mhlanga, 2024). Notably, services such as M-Pesa in Kenya have fostered entrepreneurship by offering microcredit and enabling financial transactions through mobile phones.

Fin-Tech innovations have also disrupted traditional banking models by enhancing the accessibility of financial services, particularly through mobile payment platforms and big data analytics (Cevik, 2024). These advancements have allowed Fin-Tech companies to gain a competitive edge over conventional banks, driving a shift toward digital finance. The development of new business models, particularly platform and cloud-based solutions, has enabled firms to better serve unbanked and under-banked populations (Imerman & Fabozzi, 2020). Furthermore, as highlighted by Aziz & Wahid (2019), the evolution of Fin-Tech in regions like South Africa has the role of regulatory frameworks in shaping its potential for industry disruption, although gaps in research hinder its full realisation. The broader implications of Fin-Tech on sustainable development have also been explored, particularly in the context of green finance. Integrating Fin-Tech into environmental financing strategies has shown promise in promoting sustainability, as noted by Nenavath & Mishra (2023). Innovations such as blockchain technology enhance transparency and audit ability, foster the growth of virtual currencies and overcome challenges related to geographical distance and information asymmetry in financial transactions. Technological evolution supports sustainable growth by enabling more efficient and accessible financing options for environmental projects.

Despite the transformative potential of Fin-Tech, challenges remain, particularly in regions like Sub-Saharan Africa, where energy constraints and limited financial management practices hinder its full impact (Mashamba & Gani, 2023). Sharmin Rahman (2024) further highlighted the intersection between Fin-Tech lending, financial inclusion and energy poverty, noting that policies addressing both financial and energy access are crucial for unlocking Fin-Tech's economic potential in these regions. The impact of Fin-Tech on FDI is another critical area of research. Fin-Tech facilitates cross-border transactions and enhances market transparency, thereby encouraging FDI, especially in underdeveloped markets (Loo, 2019; Shkurat, 2023). However, the regulatory context plays a crucial role in determining the effectiveness of Fin-Tech in fostering FDI, as stringent regulations may impede development (Zheng & Li, 2022). Recent studies, such as that by Fan *et al.* (2024), demonstrated that regional Fin-Tech ecosystems, such as those in China, stimulate outward FDI by assisting firms to overcome financing constraints and innovate technologically. Finally, while Fin-Tech has transformative potential, particularly in enhancing financial inclusion, driving economic growth and fostering sustainable development, its effectiveness is highly dependent on regional and regulatory factors. As global Fin-Tech ecosystems continue to evolve, further research is needed to understand the interplay between technological innovation, regulatory frameworks and economic growth.

Fin-Tech improves access to financial services for underserved populations, particularly in developing countries. Platforms such as M-Pesa in Kenya have demonstrated how mobile payment services can stimulate entrepreneurship and integrate marginalised populations into the formal economy (Mhlanga, 2024). Furthermore, digital innovations reduce the cost of accessing credit and savings, thereby facilitating economic empowerment (Xu *et al.*, 2025). Digital payments offer fast, transparent, low-cost alternatives for traditional financial systems. This has a positive impact on the efficiency of local and international transactions, thereby reducing delays and costs (Sharmin Rahman, 2024). For example, systems such as India's Unified Payments Interface have transformed retail payments through open digital infrastructure. PPL platforms and blockchain-based investment tools facilitate access to capital and democratise investment opportunities. However, the impact of PPL is sometimes mixed, particularly in developing countries where the lack of adequate regulations can limit its effectiveness (Fan *et al.*, 2024; Nenavath & Mishra, 2023). The integration of technologies such as artificial intelligence and big data analytics optimises financial decision-making processes. This reduces information asymmetries and improves transparency in financial markets, thereby attracting more foreign investment (Cumming *et al.*, 2023). Fin-Tech promotes increased global economic integration by simplifying FDI flows. These innovations strengthen financial connectivity and create an environment that is conducive to trade and investment (Fan *et al.*, 2024; Hysa *et al.*, 2022).

Our study extends these discussions by comparing the results of previous research while emphasising the regulatory and infrastructure challenges faced by many regions, unlike previous studies, which provided a more comprehensive view by integrating both financial and energy access as factors influencing the success of Fin-Tech, particularly in sub-Saharan Africa, where energy constraints remain a major obstacle (Mashamba & Gani, 2023; Sharmin Rahman, 2024). While Sharmin Rahman (2024) examined how energy poverty moderates the relationship between Fin-Tech lending, financial inclusion and economic growth, our study emphasises the need for integrated policy frameworks that simultaneously address financial, technological and energy infrastructures.

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In the realm of sustainable development, Nenavath & Mishra (2023) have explored the integration of Fin-Tech into green finance strategies, focusing on the potential of technologies such as blockchain and virtual currencies to support sustainable development projects. These studies highlight Fin-Tech's ability to overcome geographical and informational barriers. However, they fall short of addressing regional disparities in the adoption and use of Fin-Tech. Our article expands on this by delving deeper into the transformative role of Fin-Tech in promoting sustainable development, especially in underserved regions. We examine how these technological innovations can be adapted to local contexts to address specific challenges such as limited access to financial services, inadequate infrastructure and gaps in financial education. Additionally, we investigate how Fin-Tech can serve as a catalyst for both local and international initiatives aimed at achieving development goals, reducing inequalities and fostering inclusive growth.

In the context of FDI, Loo (2019) and Shkurat (2023) have demonstrated how Fin-Tech enhances cross-border transactions and market transparency, thereby stimulating FDI, particularly in underdeveloped markets. However, these studies did not fully address the regulatory dynamics that can influence or hinder this relationship. Our study fills this gap by exploring how regulatory policies can either facilitate or limit FDI flow into in-tech-driven markets. Fan *et al.* (2024) highlighted the role of Fin-Tech ecosystems in countries like China to help companies overcome financing constraints and promote internationalisation. While our study aligns with these conclusions, it makes a unique contribution by considering the dual impact of financial and technological policies in driving outward FDI and economic growth.

While previous studies have made significant contributions to understanding the role of Fin-Tech in economic growth, FDI attractiveness, financial inclusion and sustainable development, they often overlook the complexity of regulatory environments and variations between countries. Our study addresses these gaps by offering a more nuanced perspective that incorporates the specific challenges and opportunities faced by different countries. It advances the field by proposing policy recommendations that target not only financial inclusion but also access to energy and regulatory frameworks, ensuring that the full potential of Fin-Tech is realised in a sustainable and equitable manner.

Recent research in the field of artificial intelligence (AI) applications in the financial sector (Fin-Tech) is increasingly focusing on improving stock index predictions, reducing financial risks, enhancing financial inclusion and automating financial processes. AI, particularly machine learning and deep learning, is used to analyse large amounts of data in real time, allowing Fin-Tech sector players to make more informed decisions and better anticipate economic trends. These studies are part of a series of recent innovations that explore increasingly sophisticated AI methods to process massive volumes of financial and economic

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data. Other researchers have also worked on integrating AI into the Fin-Tech sector to improve banking services, digital payments and risk management. For example, the use of supervised learning models for fraud detection in online payments or the application of AI to automate portfolio management and improve investment recommendations. Moreover, research on AI applied to the Fin-Tech sector explores how these technologies can stimulate economic growth by improving access to financing, reducing transaction costs and increasing the transparency of financial markets. These advances are particularly crucial for developing countries where limited access to traditional financial services is a major obstacle to economic growth.

The study conducted by Zouaghia *et al.* (2024) highlighted the use of an automated Convolutional Neural Network (auto-CNN) model to predict fluctuations in stock market indices. This model stands out for its ability to automatically extract complex features from financial time series, surpassing traditional approaches, such as autoregressive integrated moving average (ARIMA), long short-term memory networks (LSTM) and random forest models. Using historical data on major stock indices, the model demonstrated a significant reduction in prediction errors, with an average decrease of 15% in root mean square error (RMSE) and 18% in mean absolute percentage error (MAPE). One of the strengths of this research is the speed and efficiency of the auto-CNN model, which enables real-time analyses adapted to the volatility of financial markets. The model has also proven its robustness against anomalies and noise in the data, ensuring reliable predictions even during periods of high uncertainty. The conclusions of this study highlight the transformative impact of artificial intelligence in the financial sector. The adoption of models such as auto-CNN can improve investors' decision-making, reduce risks and enhance market efficiency. Finally, the authors recommend the integration of alternative data, such as social media sentiments or economic news, to broaden the application of these approaches, particularly to cryptocurrencies or green bonds. Thus, this study illustrates the growing potential of AI to revolutionise financial services.

Empirical Validation

In this section, we empirically assess the impact of Fin-Tech on FDI and economic growth (GDP). We utilised an annual database spanning from 2014 to 2023, sourced from the World Bank Databank (https://data.worldbank.org), the IMF, the Federal Reserve Bank of St. Louis (FRED), and the OECD Library (https://www.oecd.org/en/data.html). We analysed two samples of countries: developed and emerging economies, as well as developing countries. The developed and emerging countries in our sample include Australia, Belgium, Chile, Canada, China, Denmark, Estonia, Spain, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Luxembourg, New Zealand, Norway, Poland, Portugal, Saudi Arabia, Slovenia, Singapore, Slovakia, Switzerland, Sweden, the United Kingdom, the United States, the Netherlands, the Czech Republic, and Russia. Developing countries include Brazil, Colombia, India, Indonesia, Malaysia, Mexico, the Philippines, Peru, Thailand, Turkey, Senegal, South Africa, Vietnam, Ethiopia, Kenya, Uganda, Uruguay, Albania, Argentina, Benin, Bolivia, Cameroon, Ecuador, Gambia, Mali, Nepal, Macedonia, Pakistan, Panama, Paraguay, Rwanda, Serbia, and Kazakhstan.

For our analysis, we focus on two endogenous variables: FDI and economic growth, measured by gross domestic product (GDP). We also include a range of explanatory variables, which are grouped into economic indicators, such as the interest rate (IR), exchange rate (ER), inflation rate (measured by the consumer price index (CPI)), trade balance (TB), population (POP), and information and communication technology identified by research and development (R&D). Additionally, we incorporate institutional indicators such as regulatory quality (RQ), corruption control (CC), political stability and absence of violence (PSV). Finally, we include two Fin-Tech-related indicators: digital payments (DP) and peer-to-peer lending (PPL).

Preliminary analysis

We use a range of descriptive statistical indicators, including measures of central tendency, dispersion and shape, to analyse the normality, performance, precision, symmetry and kurtosis of each variable for the sample of developed countries in this study. Table 1 presents the descriptive statistics for the different variables for the benchmark period from 2014 to 2023 on an annual basis.

Table 1. Descriptive statistics developed countries

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera
IR	1.8068	2.2071	-0.3142	7.8654	350.9732***
POP	76 183 689.1971	235 146 726.2303	5.1330	28.8621	11 290.9924***
TB	3 436 806 113.2829	21 242 297 430.8926	6.6973	49.9789	34 802.1971***
GDP	2.3952	3.4052	0.1933	9.9296	702.4678***
CPI	401.3764	3 046.1253	11.8987	147.1720	311 381.4340***
ER	74.2832	228.2561	3.8681	17.5477	3 959.1678***
RD	199 476.9433	421 361.0177	3.5423	16.2344	3 286.2449***
FDI	3.1639	81.5937	3.4350	111.6763	172 925.3980***
RQ	1.2204	0.6445	-1.0697	3.9587	80.1463***
CC	1.1892	0.8196	-0.5746	2.4320	23.9660***
PSV	0.6170	0.6050	-1.0340	3.7167	69.8587***
DP	0.0279	0.0107	0.2998	2.1626	15.4695***
PPL	0.1107	0.0929	1.5683	5.3896	226.7451***

(***) Significance at the 1% level

Notes: interest rate (IR), exchange rate (ER), inflation rate (measured by the consumer price index (CPI)), trade balance (TB), population (POP), research and development (R&D), regulatory quality (RQ), corruption control (CC), political stability and absence of violence (PSV), digital payments (DP), peer-to-peer lending (PPL)

Table 1 reveals several notable trends for developed countries during the annual study period, from 2014 to 2023. The average interest rate is low and stable, with a slight downward trend; however, the distribution shows extreme values and is not normal. The population of developed countries is characterised by a large variation, with a strong concentration of countries having exceptionally large populations, which generates a very spread out and non-normal distribution. The trade balance is also high on average but variable, with some countries having extreme trade surpluses. The GDP generally shows stable economic growth, although extreme values do exist. Inflation identified by the CPI is high and volatile, with inflation peaks in some countries, while the exchange rate , although having a low average, shows high variability. Research and development expenditures are high but disparate between countries, as are FDI expenditures which are relatively low on average but concentrated in a few countries. Overall, the normality tests indicated non-normal distributions for all economic variables, with extreme values and uneven trends.

Developed countries exhibit relatively good regulatory quality, with an average of 1.2204 and moderate variation (standard deviation of 0.6445), suggesting relative homogeneity, although some notable differences remain. The perception of corruption is also low (mean 1.1892) and relatively homogeneous among countries but shows a slight negative skewness and non-normality, as confirmed by the Jarque-Bera test. Regarding political stability, although the average is high (0.6170), the low variability (standard deviation of 0.6050) and negative skewness suggest that the majority of countries are politically stable, with a balanced distribution according to kurtosis. However, this distribution is not normal, as indicated by the significant Jarque-Bera statistic.

The sample of developed countries shows a low adoption of digital payments, with an average of 0.0279, but with some stability (standard deviation of 0.0107) and a slight concentration of countries with higher adoption (positive skewness of 0.2998). The distribution is moderately concentrated around the mean (kurtosis of 2.1626), although the Jarque-Bera statistic indicates non-normality. For PPL loans, although their adoption is low on average (0.1107), it shows greater variability (standard deviation of 0.0929) and a high concentration in certain countries (positive skewness of 1.5683). The distribution of PPL loans is marked by extreme values (kurtosis of 5.3896), and non-normality is confirmed by the highly significant Jarque-Bera statistic.

We analyse the mean, median, linear fit, symmetry, kurtosis, and normality of various macroeconomic, institutional, Fin-Tech indicators, GDP and FDI for developing countries from 2014 to 2023. This analysis is based on the measures of central tendency, dispersion and distribution shape, as presented in Table 2.

Table 2. Descriptive statistics developing countries

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera
RI	6.8048	6.9958	1.8775	12.9563	1 556.8913***
POP	96 010 679.2545	235 552 500.4792	4.8529	26.4608	8 863.3879***
TB	-190 426 467.8792	13 071 034 817.1865	**-0.1053**	10.3241	738.2007***
GDP	3.6232	3.8602	**-1.2976**	7.4170	360.8690***
CPI	156.7352	81.1973	5.1378	39.3714	19 641.3846***
ER	1 637.0631	4 555.0281	3.6024	15.5666	2 885.1474***
RD	6 724.7298	26 608.0656	5.6219	37.5266	18 129.4814***
FDI	3.0416	2.5305	1.2962	5.2379	161.2766***
RQ	-0.1838	0.4752	**-0.1265**	2.1740	10.2620***
CC	-0.4398	0.4824	1.7551	7.6205	462.9653***
PSV	-0.4822	0.7022	**-0.6919**	3.6207	31.6264***
DP	0.0320	0.0135	1.0136	3.6009	61.4729***
PPL	0.2017	0.1220	0.8111	3.8153	45.3238***

(***) Significance at the 1% level

Descriptive statistics reveal significant variability and marked asymmetries among the main macroeconomic, institutional and Fin-Tech variables of developing countries between 2014 and 2023, reflecting their economic, social and political diversity. Variables such as population and research and development investments show right-skewed distributions, influenced by countries at extreme levels. Economic variables, such as economic growth (GDP) and trade balance , indicate notable disparities, with the majority of countries showing moderate GDP and frequent trade deficits, although these vary according to national context. The interest rate shows great heterogeneity, with some countries applying exceptionally high levels to address macroeconomic challenges, such as inflation, which also exhibit significant dispersion, reflecting episodes of hyperinflation in some cases. FDI remains generally low, although some countries attract significant flows, while exchange rates exhibit high variability and are influenced by divergent monetary policies and trade imbalances. These observations highlight the structural challenges faced by developing countries and the importance of appropriate economic policies to stabilise key indicators, attract investments and strengthen their macroeconomic resilience.

Institutional indicators highlight structural weaknesses in developing countries between 2014 and 2023. The quality of regulation shows a slightly negative average (-0.1838), reflecting regulations generally perceived as insufficient, although heterogeneity was moderate (standard deviation of 0.4752). A slight left skew and kurtosis close to normal indicate that the majority of countries are clustered around this average, but the Jarque-Bera test confirms a deviation from normality. Corruption control shows a more pronounced negative average (-0.4398), suggesting a high prevalence of corruption with moderate dispersion (standard deviation of 0.4824). A right skew and high kurtosis reveal that, although rare, some countries stand out due to better corruption control, while the majority experience high levels of corruption. The average political stability (-0.4822) highlights an overall unstable environment with high variability between countries (standard deviation 0.7022). A left skew and moderate kurtosis indicate that the majority of countries are in conditions of low to moderate stability. These results highlight the importance of strengthening political and regulatory institutions to support economic development and attract investors.

Statistics on Fin-Tech reveal significant growth potential in developing countries. The adoption of digital payments remains relatively low, with an average of 0.0320 and a low standard deviation (0.0135), indicating homogeneity among the countries. A right skewness (1.0136) and moderate kurtosis (3.6009) indicate that a few countries have slightly higher adoption levels, but the majority remain underdeveloped in this area. This highlights significant potential for the expansion of digital payments, which could enhance financial inclusion and economic transactions. Similarly, PPL shows a modest average (0.2017) and a moderate standard deviation (0.1220), suggesting growing but still limited adoption in many countries. A slight right skewness (0.8111) and moderate kurtosis (3.8153) reflect better adoption in some countries, but significant heterogeneity remains. The expansion of PPL could offer a valuable alternative to broaden access to credit, particularly in regions where traditional banking services are underdeveloped. These results highlight the need to invest in digital infrastructure and create favourable regulatory frameworks to fully harness the potential of these financial innovations.

We analyse the interdependencies between GDP, FDI, macroeconomic, institutional and Fin-Tech indicators by examining the total correlation matrix for the sample of developing countries over the period from 2014 to 2023, as shown in Table 3.

Table 3 shows that the real interest rate has a positive impact on the inflation rate and research and development but shows no significant relationship with other macroeconomic, institutional or Fin-Tech variables. In contrast, population growth in developing countries supports economic growth and the expansion of the two Fin-Tech indicators. However, this population growth is negatively correlated with political stability, suggesting that an increase in population may undermine political stability without influencing other variables. The trade balance positively affects the real exchange rate, the three institutional quality indices and PPL. Economic growth, measured by GDP, plays a key role in boosting FDI, inflation, the real exchange rate and the PPL Fin-Tech indicator. However, a negative relationship is observed between economic growth and institutional indicators. Notably, economic growth in

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developing countries does not significantly alter other macroeconomic, institutional or Fin-Tech indicators included in the study.

Table 3. Correlation total matrix of developing countries

	RI	POP	TB	GDP	CPI	ER
RI	**1.0000**	-0.0102	-0.0468	0.0478	0.2515	0.0223
POP	-0.0102	**1.0000**	-0.0523	0.1009	0.0930	0.0363
TB	-0.0468	-0.0523	**1.0000**	-0.0227	0.0373	0.1289
GDP	0.0478	0.1009	-0.0227	**1.0000**	0.1190	0.1079
CPI	0.2515	0.0930	0.0373	0.1190	**1.0000**	-0.0078
ER	0.0223	0.0363	0.1289	0.1079	-0.0078	**1.0000**
RD	0.4012	-0.0106	0.0099	0.0128	0.3975	-0.0860
FDI	0.0718	-0.1468	0.0539	0.1286	-0.0029	0.0405
RQ	0.0386	-0.0316	0.1783	-0.1353	-0.1638	-0.0238
CC	-0.0399	-0.0066	0.1897	-0.0202	0.0577	-0.0586
PSV	-0.0212	-0.1996	0.2415	-0.1494	-0.2513	0.0838
DP	-0.0120	0.2428	-0.0763	0.1407	0.2323	0.0529
PPL	0.0045	0.1407	0.1080	0.0507	0.2782	0.0354

	RD	FDI	RQ	CC	PSV	DP	PPL
RI	0.4012	0.0718	0.0386	-0.0399	-0.0212	-0.0120	0.0045
POP	-0.0106	-0.1468	-0.0316	-0.0066	-0.1996	0.2428	0.1407
TB	0.0099	0.0539	0.1783	0.1897	0.2415	-0.0763	0.1080
GDP	0.0128	0.1286	-0.1353	-0.0202	-0.1494	0.1407	0.0507
CPI	0.3975	-0.0029	-0.1638	0.0577	-0.2513	0.2323	0.2782
ER	-0.0860	0.0405	-0.0238	-0.0586	0.0838	0.0529	0.0354
RD	**1.0000**	-0.1140	0.0941	0.0160	-0.1903	0.1125	-0.0302
FDI	-0.1140	**1.0000**	0.2639	0.2064	0.3092	-0.2333	-0.2168
RQ	0.0941	0.2639	**1.0000**	0.5181	0.4557	-0.1149	-0.1592
CC	0.0160	0.2064	0.5181	**1.0000**	0.5025	-0.0431	0.1124
PSV	-0.1903	0.3092	0.4557	0.5025	**1.0000**	-0.2465	-0.1433
DP	0.1125	-0.2333	-0.1149	-0.0431	-0.2465	**1.0000**	0.3894
PPL	-0.0302	-0.2168	-0.1592	0.1124	-0.1433	0.3894	**1.0000**

We examine the relationships and interdependencies among various endogenous variables, macroeconomic indicators, institutional measures and Fin-Tech indices using the total correlation matrix presented in Table 4.

Table 4. Correlation total matrix of developed countries

	RI	POP	TB	GDP	CPI	ER
RI	**1.0000**	0.0948	-0.1061	-0.0070	-0.0070	0.2015
POP	0.0948	**1.0000**	-0.0487	0.1512	-0.0259	-0.0460
TB	-0.1061	-0.0487	**1.0000**	0.0378	-0.0151	-0.0518
GDP	-0.0070	0.1512	0.0378	**1.0000**	-0.0126	-0.0116
CPI	-0.0070	-0.0259	-0.0151	-0.0126	**1.0000**	-0.0255
ER	0.2015	-0.0460	-0.0518	-0.0116	-0.0255	**1.0000**
RD	0.0258	0.8768	-0.0610	0.0829	-0.0254	0.0275
FDI	-0.0271	-0.0056	0.0474	0.0373	0.0015	-0.0003
RQ	-0.2197	-0.4365	0.2449	-0.0102	0.0672	-0.0911
CC	-0.2457	-0.3262	0.1803	-0.0264	0.0992	-0.1741
PSV	-0.1239	-0.3660	0.2213	-0.0069	0.0468	-0.0808
DP	-0.0029	0.2097	-0.1020	0.0169	0.1270	0.0797
PPL	0.1980	0.3695	0.1155	0.0909	-0.0040	0.1901

	RD	FDI	RQ	CC	PSV	DP	PPL
RI	0.0258	-0.0271	-0.2197	-0.2457	-0.1239	-0.0029	0.1980
POP	0.8768	-0.0056	-0.4365	-0.3262	-0.3660	0.2097	0.3695
TB	-0.0610	0.0474	0.2449	0.1803	0.2213	-0.1020	0.1155
GDP	0.0829	0.0373	-0.0102	-0.0264	-0.0069	0.0169	0.0909
CPI	-0.0254	0.0015	0.0672	0.0992	0.0468	0.1270	-0.0040
ER	0.0275	-0.0003	-0.0911	-0.1741	-0.0808	0.0797	0.1901
RD	**1.0000**	-0.0062	-0.2538	-0.1846	-0.2794	0.2180	0.1786
FDI	-0.0062	**1.0000**	0.0083	0.0212	0.0343	0.0024	-0.0156
RQ	-0.2538	0.0083	**1.0000**	0.9201	0.6956	-0.0253	-0.6230
CC	-0.1846	0.0212	0.9201	**1.0000**	0.6915	0.0429	-0.5234
PSV	-0.2794	0.0343	0.6956	0.6915	**1.0000**	0.0041	-0.5425
DP	0.2180	0.0024	-0.0253	0.0429	0.0041	**1.0000**	0.0564
PPL	0.1786	-0.0156	-0.6230	-0.5234	-0.5425	0.0564	**1.0000**

The total correlation matrix reveals a weak negative relationship between the monetary interest rate and the trade balance, as well as with the three institutional indicators. Conversely, a positive correlation exists between the interest rate and the exchange rate, as well as with the PPL and Fin-Tech indicator. The relationship between the interest rate and the remaining variables are negligible. We observe a positive correlation between population and economic growth, research and development, and the two Fin-Tech indicators. However, negative correlations were found between the population and the three institutional proxies. The trade balance is weakly and positively correlated with the three institutional indicators and PPL but exhibits a weak negative correlation with digital payments. From the matrix, we conclude that the correlation between economic growth, research and development, and inflation with the other explanatory variables is marginal, except for a relatively strong link between research and development and the two Fin-Tech indicators. Additionally, FDI shows no significant impact on other variables, as developed countries are primarily investors in emerging and developing markets. The three institutional indicators are weakly correlated with the macroeconomic and Fin-Tech indicators; however, they exhibit a stronger correlation with each other. Finally, while the two Fin-Tech indicators are not directly correlated, they show weak positive correlations with other variables.

Results and Discussion

The methodology of the static panel model is an econometric approach adapted to the analysis of longitudinal data, combining temporal and individual dimensions to study economic dynamics while recording the specificities of the observed units (Baltagi, 2021). It allows for controlling the unobservable characteristics specific to each entity (for example, countries), such as institutional structures or the level of financial development, thereby reducing estimation biases. Static models, particularly fixed effects and random effects are particularly effective for analysing the complex interactions between Fin-Tech, the attractiveness of FDI, and economic growth while minimising the risks of co-linearity among explanatory variables. Compared to dynamic models like the Gaussian mixture model, which require reliable instruments to address endogeneity or often less transparent nonlinear approaches, static models are better suited for relatively short periods, such as 2014 to 2023, and allow for a clear interpretation of the results (Moral-Benito *et al.*, 2019).

In the context of a comparative analysis between developed and developing countries, this methodology is ideal for capturing structural and institutional differences while incorporating the interaction terms necessary to evaluate the moderating role of Fin-Tech. Unlike cross-sectional studies, it captures the temporal dynamics of economic trends, a crucial aspect for understanding the implications of Fin-Tech over a decade. Overall, the static panel model offers a robust and intuitive compromise for analysing the moderating effects of Fin-Tech, providing actionable results to illuminate structural differences and propose recommendations tailored to the institutional realities of the studied countries.

In this article, we have clarified the moderating role of Fin-Tech in economic growth and the attractiveness of FDI. We present an original and innovative analysis, unlike previous studies that separately address the effects of Fin-Tech on economic growth or FDI attractiveness. Our study integrates these two dimensions, highlighting how Fin-Tech can not only directly stimulate the economy but also enhance the impact of FDI. Furthermore, this research compares the effect of Fin-Tech in different economic contexts (developed and developing countries), thereby identifying crucial structural differences and adapting economic policies to the specificities of each sample. Using recent data (2014–2023), this study considers significant transformations, such as the accelerated digitisation post-COVID-19 and the rise of Fin-Tech in both country categories. This article also explores the interaction between Fin-

Tech and key institutional factors, such as regulatory quality, political stability and the fight against corruption, demonstrating how these elements decisively influence the impact of Fin-Tech on growth and FDI flows.

We examine the relationship between economic growth (GDP) and various macroeconomic indicators, institutional indicators, and the two Fin-Tech measures using regression analysis. For this, we apply the static panel data methodology and estimate each relationship using the within and generalized least squares (GLS) techniques. Table 5 presents the results of these estimations for economic growth, based on the sample of developed countries over the period 2014 to 2023.

Table 5. Estimation of the long-run relationship of logarithm of economic growth in developed countries

	Within	**GLS**	**Within**	**GLS**	**Within**	**GLS**
Log(IR)	-0.0407***	-0.0234***	-0.0442***	-0.0776***	-0.0548***	-0. 0996***
Log(POP)	0.1710***	0. 3514***	0.4525***	0.5032***	0.1996***	0.25461***
Log(TB)	-0.0188***	-0.0318***	0.7173***	0. 7954***	0.5104***	2.5846***
Log(CPI)	-1.8502*	-1. 2596*	-1.3795*	-1.1811**	-1.1511**	-1.1687***
Log(ER)	0.0288**	0. 0175**	0. 0383***	0.3114***	0.2638**	0.1893**
Log(RD)	1.1171***	1.1012***	1.9104***	1.9682***	1.7173***	1.1614***
Log(RQ)	0.8563***	0. 7831***	-	-	-	-
Log(CC)	-	-	0.2491***	0.1341***	-	-
Log(PSV)	-	-	-	-	0.4663***	0.4536***
Log(DP)	0.4307***	0.4945***	0.8621***	0.7808***	0.4485***	0.3961***
Log(PPL)	1.1408***	1.1734***	0.9051***	0.5116***	1.6342***	1.1303***
Stat-Hausman	10.7485***		15.7581***		16.7485***	

(***) Significance at the 1% level; (**) Significance at the 5% level and (*) Significance at the 10% level

We estimate the long-term relationships between GDP and macroeconomic variables, Fin-Tech indicators and institutional quality proxies. The Hausman test (1978) statistics are statistically significant at the 1% risk level, indicating that the appropriate estimation method is the within method. Our findings show that research and development, population, research quality and both Fin-Tech indicators have positive and significant contributions to the economic growth of developed countries. In contrast, the remaining macroeconomic variables are negatively associated with economic prosperity. Economic growth in these countries is better supported when corruption control is effectively utilised as an institutional indicator, as it enhances the role of research and development and Fin-Tech indicators in driving economic growth. Finally, we observe that political stability and the absence of violence, as measures of institutional quality, positively influence the relationship between the trade balance, population growth, and economic development, thereby contributing to higher economic growth rates in these countries.

Our study corroborates the work of Appiah-Otoo (2025), who observed a significant positive correlation between Fin-Tech indicators and economic growth in China; however, we expand this analysis to include a broader group of developed countries, providing a more robust cross-country comparison. We confirm the conclusion drawn by Cevik (2024) that Fin-Tech is more impactful in advanced economies, but we also introduce the unique moderating role of institutional quality, specifically corruption control, in enhancing the contribution of research, development, and Fin-Tech to economic growth context of macroeconomic variables and institutional quality. Their study revealed the positive impact of Fin-Tech diffusion on GDP per capita, whereas our research goes a step further by showing how these technological advancements interact with critical institutional frameworks such as political stability and regulatory quality.

Theoretically, this study deepens our understanding of how Fin-Tech can contribute to economic growth by showing that its impact is not only direct but is also mediated through institutional quality. The positive contribution of research and development, population, regulatory quality, and Fin-Tech to economic growth in developed countries aligns with endogenous growth theory, which emphasises the importance of human capital, technological innovation and institutional settings in promoting long-term economic development. The findings suggest that Fin-Tech, as a tool of technological innovation, has the potential to significantly enhance economic growth, especially when accompanied by strong institutional frameworks. In terms of economic theory, our study reaffirms the importance of institutional quality in sustaining growth. The fact that effective corruption control enhances the positive impact of research, development and Fin-Tech on economic growth reinforces the institutional economics perspective, which emphasises the importance of good governance and efficient institutions in fostering an environment conducive to economic growth. Furthermore, the finding that political stability and the absence of violence enhance the role of macroeconomic variables, such as the trade balance and population growth in driving economic development, further supports the theories of institutional economics, particularly those linking political stability to favourable economic outcomes.

This study contributes to the existing literature by offering a more comprehensive understanding of the interdependencies between Fin-Tech, macroeconomic variables and institutional quality. Our methodology, which employed the within method after conducting the Hausman test (1978), ensures robustness in the estimation of long-term relationships, and the inclusion of corruption control as an institutional quality proxy adds a unique dimension to the analysis. Additionally, the study offers novel insights into how institutional quality can amplify the positive effects of Fin-Tech and research and development on economic growth. This perspective has not been sufficiently explored in prior studies, and by emphasising the

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moderating role of institutional factors such as corruption control, political stability, we estimate the long-term relationships between GDP and macroeconomic variables, Fin-Tech indicators and institutional quality proxies. The Hausman test (1978) statistics are significant at the 1% risk level, showing that the suitable estimation method is the within method. Our findings show that research and development, population, regulatory quality and both Fin-Tech indicators have positive and significant contributions to the economic growth of developed countries. In contrast, the remaining macroeconomic variables are negatively associated with economic prosperity. Economic growth in these countries is better supported when corruption control is effectively utilised as an institutional indicator, as it enhances the role of research and development and Fin-Tech indicators in driving economic growth. Finally, we observe that political stability and the absence of violence, as measures of institutional quality, positively influence the relationship between trade balance, population growth and economic development, thereby contributing to higher economic growth rates in these countries.

We apply the same static panel methodology to estimate the relationships between FDI and various macroeconomic indicators, institutional quality proxies and the two Fin-Tech measures. Using the within and GLS techniques, the results are presented in Table 6, and for regulatory quality, we provide a more nuanced view of the drivers of economic prosperity in developed countries. Our study also introduces the possibility of applying these findings to policymaking. Specifically, our research suggests that policymakers in developed countries should prioritise strengthening institutional frameworks, – especially in terms of reducing corruption and promoting political stability – to maximise the potential of Fin-Tech and other technological innovations in boosting economic growth. We apply the same static panel methodology to estimate the relationships between FDI and various macroeconomic indicators, institutional quality proxies and the two Fin-Tech measures.

Table 6. Estimation of the long-run logarithm relationship of FDI attractiveness to developed countries

	Within	**GLS**	**Within**	**GLS**	**Within**	**GLS**
Log(IR)	-0.8659**	-0.4732***	-0.7983***	-0.5124***	-0.8111***	-0.6458***
Log(POP)	0.2601	0.2458	0.1894	0.1247	0.2004	0.1287
Log(TB)	0.3449**	0.2497**	0.1027*	0.2145***	0.6978**	0.5647*
Log(CPI)	0.8422***	0.7548***	0.1812***	0.2147***	0.6247***	0.6571**
Log(ER)	0.2014**	0.3145***	0.0049*	0.0054*	0.0047*	0.0021*
Log(RD)	0.8457***	0.7412***	0.7371**	0.7549*	0.1241**	0.2145**
Log(RQ)	0.7769***	0.4581***	-	-	-	-
Log(CC)	-	-	0.0399	0.0348	-	-
Log(PSV)	-	-	-	-	0.5417***	0.5124***
Log(DP)	3.3197***	1.4825***	2.9427	2.5784	3.0568***	1.2457***
Log(PPL)	1.8419***	1.6412***	3.9437	3.2471	1.9481***	1.7426***
Stat-Hausman	10.2456***		12.4871***		13.4573***	

(***) Significance at the 1% level; (**) Significance at the 5% level and (*) Significance at the 10% level

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We employ the static panel model methodology to examine the potential relationships between FDI, Fin-Tech, macroeconomic indicators and institutional measures, analysing each indicator in relation to its defining variables. To achieve this, we utilise appropriate estimation techniques, including the Hausman test (1978), which help to determine the nature of the individual effects. Our analysis began with estimating a static fixed effects model, followed by conducting the Hausman test (1978). The fixed effects model proved valuable in controlling country-specific and year-specific effects, as well as addressing potential issues of multi-collinearity. The first step in the econometric process involved testing the model's suitability, which played a key role in interpreting the results.

Hausman's test (1978) statistics are statistically significant at the 1% level, confirming that these relationships are best interpreted using the within procedure, as it decomposes the errors and fixes the individual effects. The results demonstrate that most macroeconomic indicators contribute positively and significantly to FDI, regardless of the institutional indicator used. However, the interest rate has a negative and significant impact on FDI, while the economic growth shows a positive but statistically insignificant effect. We observe that the quality of regulation and political stability (as indicated by the absence of violence) have highly significant positive effects on FDI, whereas the corruption control has no discernible impact. In terms of Fin-Tech, both digital payment and PPL indices have substantial positive effects on FDI when combined with either regulatory quality or political stability as institutional measures. However, these indices have no significant influence on FDI when corruption control is used as the institutional proxy.

Our study builds upon previous work by Ali *et al.* (2024), who identified a positive and significant relationship between Fin-Tech parameters and FDI in BRICS economies. While their research focused on emerging markets, we extend their findings by demonstrating that political stability significantly enhances the positive relationship between Fin-Tech and FDI in developed economies. This comparative approach is novel, as it shifts the focus from developing to advanced economies, where the institutional and economic environments are markedly different. In addition, our findings align with those of Tokhtamysh (2020), who found that the development of Fin-Tech markets, particularly venture capital investments in Fin-Tech projects, had a significant impact on FDI. We corroborate their conclusion that Fin-Tech can play a crucial role in attracting foreign investments, especially in large, economically advanced countries such as the United States and the United Kingdom. However, our study provides a more granular view by specifically analysing how the combination of Fin-Tech development and institutional factors such as political stability and regulatory quality influences FDI in developed countries.

Our results provide valuable insights into the theoretical framework of FDI determinants, particularly within the context of institutional economics. We find that the quality of regulation and political stability significantly enhance the relationship between Fin-Tech and FDI, which aligns with institutional theories that stress the importance of strong governance in attracting foreign capital. This finding suggests that institutions are not only important in shaping the economic environment but also in determining how effectively Fin-Techs can spur FDI. In contrast, our study reveals that corruption control does not have a discernible impact on FDI, a result that diverges from previous studies where corruption was often considered a significant barrier to investment. This outcome can be interpreted through the lens of the 'institutional void' hypothesis (Rodrigues, 2013), which posits that in some developed economies, institutional inefficiencies like corruption may have less impact due to stronger, more established legal frameworks, or due to the high relative attractiveness of the economy itself. Moreover, the insignificant relationship between the economic growth rate and FDI in our study is in line with the argument that 'FDI is more attracted to stable environments' rather than growing economies. This supports the idea that factors like political stability and regulatory quality, rather than pure economic growth rates, are more influential in attracting FDI.

This study advances the current understanding by combining multiple institutional quality proxies, macroeconomic variables and Fin-Tech indicators to examine their collective effect on FDI. Our use of the static fixed-effects model, along with the Hausman test (1978) to determine the most appropriate model, provides a rigorous methodological approach that accounts for both country-specific and year-specific effects. The significant positive effect of regulatory quality and political stability on FDI when coupled with Fin-Tech development is a unique contribution, demonstrating the importance of institutional factors in maximising the potential of Fin-Tech to attract foreign investment. Additionally, our study offers a novel perspective by demonstrating that corruption control, which has traditionally been seen as a key driver of FDI, does not have a significant impact in developed economies where institutional frameworks are typically more robust. These finding challenges conventional wisdom and suggests that in more advanced economics the focus may need to shift toward other institutional factors, such as regulatory quality and political stability, to enhance FDI inflows. Furthermore, the finding that digital payment systems and PPL indices have substantial positive effects on FDI when paired with either regulatory quality or political stability provides practical implications for policymakers. It suggests that fostering an environment where Fin-Tech can thrive, especially through political stability and sound regulation, can serve as a strategic lever for attracting foreign investment.

We now examine the impact of FinTech and macroeconomic indicators on economic growth—measured by Gross Domestic Product (GDP)—using one of the three institutional quality indices discussed in our study, for a sample of developing countries from 2014 to 2023 on an annual basis. The results of this analysis are presented in Table 7.

Table 7. Long-run estimation of the logarithm of economic growth in developing countries

	Within	GLS	Within	GLS	Within	GLS
Log(IR)	0.0243***	0.0487***	0.0471***	0.0421***	0.0278***	0.0514***
Log(POP)	0.7495***	0.6548***	0.7218***	0.7748***	0.8427***	0.5436***
Log(TB)	-0.4561**	-0.2387**	-0.4782***	-0.5782***	-0.4728***	-0.4829***
Log(CPI)	0.8741***	0.5473***	0.7692***	0.2480***	0.3642**	0.1272**
Log(ER)	0.6571***	0.5875***	0.5752***	0.5587***	0.6521***	0.5481***
Log(RD)	0.0342***	0.0417***	0.0781**	0.0024***	0.0027*	0.0102**
Log(RQ)	0.8984***	0.8191***	-	-	-	-
Log(CC)	-	-	0.0422***	0.0428***	-	-
Log(PSV)	-	-	-	-	-0.6733***	-0.6706***
Log(DP)	1.4720***	1.6784***	2.2898***	1.0951***	2.3364**	3.4014***
Log(PPL)	-1.4996***	-0.8416***	-1.0988***	-0.4146***	-1.3712***	-0.7716***
Stat-Hausman	16.5741***		21.5842***		25.4872***	

(***) Significance at the 1% level; (**) Significance at the 5% level and (*) Significance at the 10% level

The Hausman test (1978) statistics are statistically significant at the 1% risk level, indicating that we accept only the relationships estimated by the within method, as the individual effects are fixed. All macroeconomic indicators contribute positively to the economic growth of developing countries, except for the trade balance deficit, which hinders growth, as its coefficient is negative and significant across various institutional indicators. The quality of regulation has a positive impact on the economic prosperity of these countries. Additionally, digital payments are associated with an increase in the economic growth rate of developing countries, as their coefficient is strictly positive and significant. In contrast, PPL has a significant negative effect on economic growth in these countries.

Our findings are consistent with those of Adewuyi (2024), who observed limited impact of Fin-Tech on GDP per capita in Nigeria. While their research focused specifically on Nigeria, our study extends this observation to a broader set of developing countries, highlighting that the impact of Fin-Tech can vary widely, with both positive and negative effects. This suggests that, while Fin-Tech holds significant potential for fostering economic growth, its effectiveness is contingent upon factors such as the type of technology employed, the maturity of the financial ecosystem, and the institutional context in which it operates. Our study reinforces several key theoretical frameworks in economic growth and institutional economics at the same time introducing new dynamics that complicate the standard models.

Specifically, the positive relationship between digital payments and economic growth in developing countries aligns with endogenous growth theory which posits that technological advancements, such as those seen in the Fin-Tech sector, contribute to long-term economic development by increasing productivity and improving access to financial services. The negative relationship observed between PPL and economic growth introduces a unique theoretical insight. While PPL is often considered a valuable tool for expanding access to credit and fostering entrepreneurship, its negative impact in developing countries suggests that its effectiveness may be contingent on factors such as financial literacy, institutional maturity and the regulatory environment. This result may be explained by the idea of 'financial exclusion' in certain contexts, where the risks associated with informal lending platforms, lack of adequate regulation or weak legal frameworks may offset the potential benefits, ultimately hindering economic growth. The negative effect of the balance of payments deficit on economic growth is another important finding, which is consistent with traditional economic theories that emphasise the detrimental impact of external imbalances on a country's financial stability and growth prospects. This reinforces the notion that macroeconomic stability – particularly in terms of external accounts – is crucial for sustainable development in developing economies.

One of the key contributions of this study is its nuanced examination of how different types of Fin-Tech technologies (digital payments versus PPL) interact with macroeconomic and institutional variables to shape economic outcomes in developing countries. This dual effect of Fin-Tech has not been thoroughly explored in the existing literature, and our results highlight the complexity of these relationships, offering a more refined understanding of the role of technology in economic development. Furthermore, the study offers a methodological contribution by employing the static fixed-effects model to control for individual and time-specific effects while utilising the Hausman test (1978) to ensure the robustness of the results. The use of this rigorous econometric approach ensures that our findings are reliable and can be generalised to a broader set of developing economies. By testing the model's suitability and confirming that the within method is the most appropriate, we provide robust evidence for the relationships between the variables, which enhances the credibility of the conclusions drawn. The finding that the quality of regulation has a positive impact on economic growth in developing countries contributes to the institutional economics literature by emphasising the importance of sound regulatory frameworks. This result suggests that Fin-Tech innovations, when combined with effective regulation, can act as catalysts for economic growth. However, the fact that corruption control had no significant effect in this context suggests that other dimensions of institutional quality – such as regulatory enforcement and political stability – may be more critical for fostering growth in developing countries.

We examine the contribution of Fin-Tech, macroeconomic indicators and each institutional indicator to FDI in the developing countries, as presented in Table 8.

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Table 8. Estimation of the long-run logarithm relationship of FDI attractiveness to developing countries

	Within	GLS	Within	GLS	Within	GLS
Log(IR)	0.0395***	0.0922***	0.0475***	0.0312***	0.0350***	0.0342***
Log(POP)	0.7458***	0.8452***	0.7481***	0.7549***	0.7084***	0.6824***
Log(TB)	0.0215**	0.0125***	0.0124***	0.0097***	0.0082***	0.0069***
Log(CPI)	0.0063***	0.0133***	0.0043***	0.0055***	0.0059***	0.0042***
Log(ER)	0.0105***	0.0124***	0.0105***	0.0121***	0.0113***	0.0112***
Log(RD)	0.0075***	0.0086***	0.0203***	0.0143***	0.0201***	0.0107***
Log(RQ)	0.4429***	0.3922***	-	-	-	-
Log(CC)	-	-	0.1903***	0.2174***	-	-
Log(PSV)	-	-	-	-	0.9371***	0.8425***
Log(DP)	0.9809***	0.6865***	0.8168***	0.8451***	0.8194***	0.7421
Log(PPL)	0.6464***	0.7237***	0.7475***	0.8168***	0.9066***	0.8452
Stat-Hausman	19.2489***		22.4594***		23.1749***	

(***) Significance at the 1% level; (**) Significance at the 5% level and (*) Significance at the 10% level

Hausman's test (1978) statistics are statistically significant at the 1% risk level, so we retain only the relationships estimated using the within technique. All macroeconomic indicators show a marginal contribution to FDI, except for the population growth rate, which has a significant impact on these investments. The various institutional measures have a positive and significant influence on FDI. Furthermore, both institutional indicators exhibit strong sensitivity to FDI, as their coefficients are positive and significant. The consistent evidence from studies such as Ahmed & Jahanzeb (2021), Islam *et al.* (2020), Chen *et al.* (2020), Khan & Khan (2019) and Sirag *et al.* (2018), further supports our findings. These studies generally highlight the importance of institutional and macroeconomic stability in attracting FDI and emphasise that countries with better institutional frameworks, regulatory quality and political stability tend to attract higher levels of foreign investment. The positive influence of institutional quality on FDI inflows in our study is consistent with these results, particularly in the context of middle-income economies where the potential for growth is higher. Our study also supports the theoretical frameworks on FDI that highlight the importance of macroeconomic stability and institutional quality. Dunning's eclectic paradigm (Dunning, 2000), which suggests that FDI is attracted by a combination of ownership, location and internalisation advantages, is reinforced by our findings. We see that institutional factors such as regulatory quality and political stability contribute significantly to FDI inflows, suggesting that these factors are vital location advantages that foreign investors seek. This is particularly evident in our results, where the significance of institutional quality in attracting FDI aligns with Dunning's framework (Dunning, 2000), reinforcing the idea that stable and supportive institutional environments provide the right conditions for foreign investment to flourish.

The significant impact of population growth on FDI inflows in our study presents a useful addition to the FDI literature. Population growth, often seen as a proxy for market potential and human capital availability, is a critical determinant of FDI in middle-income countries. As countries experience population growth, they become more attractive to foreign investors due to the increasing size of the domestic market and the potential for labour force expansion. This finding contributes to the literature by adding empirical evidence to the argument that demographic factors play a crucial role in attracting FDI, particularly in emerging economies with high growth potential. The strong sensitivity of FDI to institutional quality, as evidenced by the positive and significant coefficients of the institutional measures in our study, introduces an important theoretical perspective on the role of governance and regulatory frameworks in attracting foreign investment. Our results suggest that institutional quality plays a key role in creating a favourable investment climate. This finding is consistent with institutional theory, which argues that well-functioning institutions, including the legal system, regulatory bodies and political stability, are essential for fostering economic activities such as FDI. Additionally, the study builds on the classical and neoclassical theories of economic development, which argue that economic factors, such as financial development, macroeconomic stability and institutional frameworks, drive long-term growth and attract foreign investments. The positive and significant influence of institutional measures on FDI in our study underscores the importance of these factors in shaping the FDI landscape, particularly in middle-income economies.

The methodological approach employed in this study, which utilises the Hausman test (1978) and the within technique, provides several unique advantages. The use of the static fixed-effects model, with the Hausman test (1978) ensuring the appropriate use of the within estimator, ensures that we account for country-specific and year-specific effects, which is particularly important when dealing with cross-country data. By selecting the within estimator based on the Hausman test (1978), we avoid potential biases that could arise from random effects or omitted variable bias, thus increasing the robustness of our results. Moreover, our study's focus on macroeconomic variables, institutional quality and their interaction with financial development offers a more nuanced understanding of the factors influencing FDI inflows. While previous studies have focused on financial development in isolation, our approach considers a broader set of determinants, providing a more comprehensive view of what drives FDI. This perspective is particularly valuable in middle-income economies, where multiple factors – ranging from demographic trends to institutional quality – work together to shape the attractiveness of the investment climate.

This study makes several important contributions to the existing body of literature on FDI and economic development. By highlighting the positive effects of population growth and institutional quality on FDI inflows, we expand our understanding of the key factors that make countries attractive to foreign investors. The dual emphasis on financial development and institutional quality offers new insights into how these factors interact to foster a favourable investment climate, particularly in the context of middle-income countries. Our study's findings also offer a deeper understanding of the sensitivity of FDI to institutional quality, suggesting that countries with stronger institutions are more likely to benefit from the positive effects of financial development. This insight advances the literature by showing that institutional factors are not only complementary to financial development but are also critical in unlocking the full potential of FDI. As a result, policymakers in developing economies can better prioritise improvements in institutional quality to enhance their attractiveness to foreign investors.

This study provides robust empirical evidence that both macroeconomic factors and institutional quality play significant roles in attracting FDI. By showing that population growth, institutional quality and financial development are key determinants of FDI inflows, our findings contribute to the literature on FDI and economic development, particularly in middle-income countries. The methodological rigour employed in this study strengthens the reliability of the findings, while the insights gained from this research can guide policymakers in developing economies who are seeking to improve their investment climate. Ultimately, our study advances the corpus of knowledge by offering new perspectives on the interplay between institutional quality, financial development and FDI.

Conclusion, Limitations and Future Research Directions

This study highlights the significant role of Fin-Tech in attracting FDI and driving economic growth (GDP) in both developed and developing countries. Fin-Tech innovations have disrupted traditional financial services by creating new products, streamlining processes and introducing innovative business models. Research by Boratynska (2019), Chemmanur *et al.* (2020), and Mitra & Karathanasopoulos (2020) demonstrated that Fin-Tech integration reduces transaction costs, enhances financial inclusion and provides access to financial services for historically excluded populations. Cevik (2024) and Mhlanga (2024) further confirmed that technologies like big data, digital platforms and mobile finance have improved financial inclusion, particularly in developing countries. Examples such as M-Pesa in Kenya demonstrate the tangible benefits of Fin-Tech in fostering entrepreneurship and economic growth. Recent studies by Shkurat (2023), Xu *et al.* (2025) and Fan *et al.* (2024) emphasised the crucial role of Fin-Tech in driving FDI. Fin-Tech simplifies cross-border transactions, enhances transparency and integrates digital finance into FDI flows, with technologies like blockchain and digital payments strengthening global financial interconnectedness. This promotes inclusive and sustainable economic growth, especially in sectors like agriculture in China. The synergy between Fin-Tech and FDI creates a virtuous cycle that fosters innovation, competitiveness and more inclusive development. However, the impact varies based on each

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country's economic and technological context, highlighting the need for tailored approaches to leverage Fin-Tech for FDI growth.

This study analyses a panel of 69 countries – 36 developed and emerging economies and 33 developing countries – over the 2014–2023 period to empirically assess the impact of Fin-Tech on FDI and economic growth (GDP). Using FDI and GDP as dependent variables, the analysis includes macroeconomic indicators (interest rates, exchange rates, inflation, population), ICT proxies (R&D), institutional quality (regulation, corruption control, political stability), and Fin-Tech variables (digital payments and PPL). Descriptive statistics reveal that most variables do not follow a normal distribution, with significant skewness, excess kurtosis and high standard deviations, particularly for macroeconomic and endogenous variables, indicating information asymmetry and volatility. Conversely, institutional and Fin-Tech indicators exhibit better statistical consistency with lower variability. The findings also show that macroeconomic and endogenous variables have higher means compared to institutional and Fin-Tech indicators across both country groups.

The long-term analysis for developed countries reveals that research and development, population, regulatory quality and Fin-Tech indicators significantly boost economic growth, while other macroeconomic variables have a negative impact. Effective corruption control and political stability further enhance the positive effects of research and development, Fin-Tech and demographic growth on economic development. These findings are consistent with previous studies, such as Song & Appiah-Otoo (2025), Cevik (2024) and Kanga *et al.* (2021), which also highlighted the growth-enhancing role of Fin-Tech.

Using a static panel model and the Hausman test (1978), this analysis examines the long-term relationships between FDI, macroeconomic indicators, Fin-Tech measures and institutional factors in developed countries. The results show that most macroeconomic indicators positively impact FDI, except for the real interest rate which negatively affects it, and the economic growth rate which has no significant impact. Regulatory quality and political stability have strong positive effects on FDI, while corruption control shows no effect. Fin-Tech indicators, including digital payments and PPL, positively influence FDI when combined with regulatory quality or political stability but not with corruption control. These findings align with previous studies by Ali *et al.* (2023) and Tokhtamysh (2020), highlighting Fin-Tech's role in promoting FDI in developed economies.

Hausman test (1978) statistics confirmed that the within method provides valid results for developing countries where individual effects are fixed. The findings indicate that most macroeconomic indicators, except for the trade balance deficit, positively impact economic growth in developing countries. Regulatory quality and digital payments contribute to economic prosperity, while PPL has a negative effect. These results align with the research by Khan & Khan (2019) and Nguedie (2018) , which emphasised the role of ICT in economic development, although Fin-Tech variables show mixed effects. Additionally, Adewuyi (2024) found a limited impact of Fin-Tech on GDP per capita in Nigeria; a finding consistent with this study.

Based on significant Hausman test (1978) statistics at the 1% level, the study relies on the within method to estimate relationships for developing countries. Most macroeconomic indicators have a marginal impact on FDI, except for the demographic growth rate, which has a significant effect. Institutional measures, particularly regulatory quality and political stability, positively influence FDI, with strong and significant coefficients. These findings align with studies by Nguyen & Lee (2021), Ahmed & Jahanzeb (2021), Islam *et al.* (2020) and Khan & Khan (2019), which also highlighted the role of financial development in stimulating FDI, particularly in middle-income economies.

This study offers key recommendations for policymakers, emphasising the importance of a strong regulatory framework, political stability and anti-corruption measures to enhance the attractiveness of FDI. It provides foreign investors with tools to identify promising markets by evaluating a country's Fin-Tech ecosystem and its interaction with institutional factors, highlighting the role of Fin-Tech in boosting transparency and investor confidence. The research also suggests strategic opportunities for Fin-Tech companies to collaborate with governments to promote financial inclusion and economic modernisation. Academically, our article contributes to the literature by linking Fin-Tech to economic growth and FDI attractiveness, responding to calls for further exploration of the interaction between financial innovations and institutional contexts in driving capital flows and economic development.

This study has several limitations. It is based on a static dataset that does not account for the temporal dynamics of Fin-Tech's evolution. The analysis assumes long-term effects that require further exploration, particularly in a more diverse sample of countries with varying socioeconomic development paths. Additionally, a deeper examination of the internal mechanisms through which Fin-Tech influences economic growth and FDI is needed. Longitudinal studies could offer valuable insights into the relationship between regulatory changes, Fin-Tech implementation and their long-term economic effects. Furthermore, risks associated with Fin-Tech, such as cyber-security threats and regulatory challenges, need to be considered for a balanced approach to growth and risk management. Future research will focus on developing inclusive and sustainable growth strategies that leverage Fin-Tech's benefits while mitigating its risks.

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A Hybrid AI Model Combining RF and SVM for Accurate Sales Prediction in SMEs to Support Digital Transformation

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Abstract: Small and Medium Enterprises (SMEs) are increasingly adopting digital transformation to enhance their competitive advantage and operational efficiency. Accurate sales prediction is crucial for informed decision-making and business strategy optimisation. This research presents a Hybrid AI model, which combines the machine learning techniques of Random Forest (RF) and Support Vector Machine (SVM). Unlike traditional ensemble methods, this hybrid model leverages AI-driven decision-making processes to provide a more intelligent, adaptive, and accurate approach to sales forecasting in SMEs. By integrating RF's ensemble learning power with SVM's robust classification abilities, the model effectively addresses sales prediction challenges in dynamic business environments. The hybrid model was evaluated using key statistical metrics, achieving a Mean Squared Error (MSE) of 0.7254, Mean Absolute Error (MAE) of 0.4605, and an R-squared (R^2) value of 0.99999, indicating outstanding predictive accuracy and a near-perfect fit to the data. These results demonstrate the model’s capacity to capture complex sales data relationships, proving its practical applicability for sales forecasting. This study highlights the potential of hybrid AI models in advancing sales forecasting techniques, particularly in the context of digital transformation for SMEs.

Keywords: Hybrid Artificial Intelligence, Random Forest, Support Vector Machine, Sales Prediction, Digital Transformation.

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Introduction

The widespread adoption of digital technologies in business operations has driven substantial changes in how Small and Medium Enterprises (SMEs) formulate and pursue their strategic objectives (Gaertner *et al*., 2024). In particular, the accurate forecasting of sales has become an essential element in optimising operations, improving decision-making, and enhancing competitiveness (Sun & Li, 2024). Given the increasingly volatile market dynamics and diverse consumer behaviours, the ability to generate reliable sales predictions is critical for SMEs, especially as they navigate the complexities of digital transformation (Ojukwu *et al*., 2025). Accurate sales forecasting enables SMEs to better manage inventory, allocate resources efficiently, and formulate data-driven strategies to foster sustainable growth (Pandey *et al*., 2024).

Conventional methods for sales forecasting, including time-series analysis and linear regression techniques, often fall short in addressing the non-linear, multi-dimensional relationships inherent in contemporary sales data (Ahaggach *et al*., 2024). These conventional techniques frequently struggle to account for the myriad of factors influencing sales outcomes, including market trends, seasonality, and consumer preferences. Consequently, there has been an increasing focus on utilising advanced machine learning (ML) algorithms to improve the precision of sales forecasts (Gupta & Agarwal, 2024).

In order to give SMEs a more accurate and reliable sales forecasting technique, this study suggests a novel hybrid Artificial Intelligence (AI) model that combines the capabilities of Random Forest (RF) and Support Vector Machine (SVM) algorithms. One ensemble learning technique that is particularly good at managing high-dimensional data and identifying intricate relationships between variables is Random Forest (Jothiraj *et al*., 2024). It reduces overfitting and enhances model generalisation by combining predictions from several decision trees. On the other hand, Support Vector Machine, a potent supervised learning algorithm, creates the best decision boundaries in a high-dimensional feature space, making it very useful for classification and regression problems (Pai *et al*., 2024). The integration of these two algorithms aims to leverage the complementary strengths of RF and SVM, resulting in a more reliable forecasting model capable of better predicting sales outcomes under varying conditions (Ganesan, 2024; Sharma *et al*., 2024).

RF is an ensemble learning method that excels in handling large and complex datasets. It reduces overfitting by aggregating the predictions of multiple decision trees, resulting in a more stable and robust model against noise (Maindola *et al*., 2024; Miao & Xu, 2024). However, RF can struggle with capturing more intricate non-linear relationships in data.

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On the other hand, SVM is highly effective for handling classification and regression problems with complex and non-linear decision boundaries (Wong, 2023). SVM works well in high-dimensional spaces and is particularly useful in identifying the optimal margin between classes. However, it is sensitive to noise in data and heavily reliant on proper hyperparameter tuning (Mittal *et al.*, 2024).

The Hybrid RF-SVM Model combines the strengths of both algorithms. By merging the predictive outputs of RF and SVM, the model benefits from RF's ability to handle large-scale, high-dimensional data and SVM's proficiency in handling non-linear relationships, resulting in a more accurate and reliable forecasting model (Chen, 2023; Orra *et al.*, 2023).

Sales forecasting plays a crucial role in the strategic decision-making processes of SMEs. Traditional methods often fall short in addressing the complexities of modern market dynamics, such as seasonality, consumer preferences, and market trends. ML techniques have proven to be more effective in capturing these complexities. In this context, the use of RF and SVM algorithms has gained popularity for their ability to handle large datasets and capture non-linear relationships in sales data.

While RF and SVM are strong machine-learning techniques for predictive modelling, the integration of both methods within this hybrid AI model enables a more intelligent and adaptive approach to sales forecasting. This model contributes to intelligent decision-making automation by analysing and predicting sales trends with high accuracy. The adaptive learning capabilities of the model allow it to adjust to new data, such as changing consumer behaviours or market conditions, continuously improving the predictions over time.

The primary purpose of this research is to empirically evaluate the efficacy of the proposed RF-SVM hybrid model in forecasting sales for SMEs, with a special focus on evaluating its predictive accuracy to standard sales forecasting techniques (Islam *et al.*, 2024). The results are anticipated to yield significant insights into how advanced machine learning models can assist SMEs in their digital transformation, facilitating more informed decision-making and the optimisation of operational processes in a progressively competitive and digitally oriented marketplace (Anchuri, 2024).

By incorporating both theoretical and practical considerations, the purpose of this study is to improve the body of knowledge already available on AI-driven forecasting models, with a focus on how applicable they are to SMEs in the context of digital transformation (Ocran *et al.*, 2024; Shukla, 2024). With this empirical assessment, we hope to show how AI methods might improve decision-making, helping SMEs better negotiate the intricacies of the contemporary business landscape (Shaikh, 2024).

Literature Review

Sales forecasting has become an essential part of company strategy support, particularly for SMEs, as global market complexity increases. Various approaches have been applied in sales forecasting, ranging from traditional methods to ML-based techniques. Among these approaches, RF and SVM algorithms have shown promising results, both in sales forecasting and in other applications involving large and complex datasets (Sharma *et al.*, 2024).

One ensemble learning technique that is well known for handling high-dimensional data and reducing the problem of overfitting is RF. Several studies have demonstrated the effectiveness of RF in predicting variables dependent on numerous interacting factors (Tran, 2023). Dudek (2022) showed that RF, by combining the decisions of multiple trees, provides more stable and accurate predictions compared to traditional methods. Further research by Zhao *et al.* (2024) showed that RF's proficiency with handling unstructured data and capturing intricate relationships between variables makes it an excellent choice for sales forecasting. The main advantage of RF lies in its generalisation ability, making it suitable for datasets exhibiting non-linear characteristics typically found in sales forecasting.

However, SVMs have demonstrated efficacy in classification and regression tasks, especially when there are complex distributions and high-dimensional data (Mittal et al., 2024). Guo *et al.* (2024) introduced SVM as one of the most robust algorithms for identifying the optimal margin between classes, which can be extended to regression problems for building resilient predictive models. Research by Ganguly & Mukherjee (2024) indicated that SVM outperforms traditional linear regression models in sales forecasting, particularly when data has more intricate and non-linear relationships. Additionally, Kumar *et al.* (2024) confirmed that SVM can handle noisy data, which is often encountered in sales datasets, thus providing more accurate predictions.

The application of hybrid models to improve predictive performance by fusing the advantages of several algorithms has been the subject of recent research. Tao *et al.* (2020) suggested a hybrid model that forecasts stock values by merging SVM with Whale Optimisation, demonstrating notable accuracy gains over using either method alone. This research highlighted the importance of leveraging various approaches to build a more robust prediction model, especially when dealing with dynamic data influenced by multiple external factors.

In the context of sales forecasting for SMEs, Islam *et al.* (2024) developed a hybrid RF XGBoost-LR model to forecast product demand in the retail industry. Their findings showed that, especially in the face of turbulent market conditions, combining RF and SVM improved forecasting accuracy when compared to more conventional models like linear regression. This study emphasised that hybrid models can handle uncertainty and market dynamics more effectively, thus offering more reliable sales predictions.

Recent studies have investigated various machine learning models to enhance sales prediction in retail analytics. Ganguly & Mukherjee (2024) employed Random Forest, which demonstrated a strong ability to capture intricate patterns within complex retail datasets, achieving a prediction accuracy of 0.945. However, they acknowledged that the inherent complexities of retail data still posed a challenge. In a different approach, Zhu (2025) developed a hybrid model combining Variational Mode Decomposition (VMD) with SVM to address the issues of noise and volatility in time-series data, attaining a performance metric of 0.9214. Despite the model's robustness in dynamic market environments, challenges in handling market fluctuations remained. Similarly, AbdElminaam *et al.* (2024) demonstrated the effectiveness of RF in sales prediction, achieving an accuracy of 0.97 and offering valuable insights for retail decision-making. These findings underscore the effectiveness of RF in retail forecasting, while highlighting its limitations in dealing with complex datasets and non-linear relationships. The hybrid approach, while promising for managing noise and volatility, requires further refinement to improve its adaptability to market changes. Collectively, these studies emphasise the need for selecting appropriate machine-learning models based on the specific challenges presented by retail data. Table 1 provides a comparison of various machine-learning models used in sales forecasting, specifically for SMEs:

Table 1. Comparison of ML Models in Sales Forecasting for SMEs

Study	Model Used	Key Findings	Performance Metric	Limitations
Sharma *et al.* (2024)	Random Forest	RF shows promise in sales forecasting and complex data handling, especially for large datasets.	N/A	Lack of direct comparison to other algorithms in specific sales forecasting contexts
Tran (2023)	Random Forest	RF is effective in predicting variables dependent on numerous interacting factors.	N/A	Challenges in managing extremely high-dimensional data
Dudek (2022)	Random Forest	RF provides more stable and accurate predictions by combining decisions from multiple trees, outperforming traditional methods.	N/A	Overfitting in specific, small datasets
Zhao *et al.* (2024)	Random Forest	RF excels in handling unstructured data and capturing complex relationships between variables, making it ideal for sales forecasting.	N/A	May not generalise well to new or unstructured types of data beyond retail

Study	Model Used	Key Findings	Performance Metric	Limitations
Mittal *et al.* (2024)	Support Vector Machine	SVM is effective in handling high-dimensional data and performing regression tasks, especially with complex distributions.	N/A	Overfitting risk in noisy or highly unbalanced data sets
Guo *et al.* (2024)	Support Vector Machine	SVM identifies the optimal margin for classification and regression, enhancing predictive model resilience.	N/A	Sensitivity to choice of kernel and parameters
Ganguly & Mukherjee (2024)	Support Vector Machine	SVM outperforms linear regression models in sales forecasting, especially with non-linear and complex data relationships.	N/A	Difficulties with parameter tuning, especially with noisy data
Kumar *et al.* (2024)	Support Vector Machine	SVM can handle noisy sales data, improving prediction accuracy compared to simpler methods	N/A	Limited scalability to large datasets
Tao *et al.* (2020)	Hybrid SVM with Whale Optimisation	Hybrid model combining SVM with Whale Optimisation improves accuracy in stock forecasting.	N/A	Applicability restricted to specific domains like stock forecasting
Ganguly & Mukherjee (2024)	Random Forest	Successfully addresses the complexities of retail datasets, capturing intricate patterns and improving prediction accuracy significantly.	0.945	The complexities of retail datasets
Zhu (2025)	Hybrid model combining Variational Mode Decomposition and Support Vector Machine	The challenges of noise and volatility in time-series data.	0.9214	A robust solution for dynamic market changes.
AbdElminaam *et al.* (2024)	Random Forest	The effectiveness of machine learning models in sales prediction.	0.97	Offer valuable insights for retail decision-making

Additionally, other research has looked into how hybrid models might be used in the context of SMEs' digital transformation. Mohd *et al.* (2023) discussed the role of hybrid models in enabling SMEs to leverage big data to improve decision-making processes. By employing AI techniques such as RF and SVM, SMEs can achieve more accurate sales forecasts, allowing them to adjust business operations dynamically. This is particularly critical in the context of rapid digitalisation, where data plays a key role in determining business success.

In contrast, this study proposes a novel Hybrid AI model that combines the strengths of both RF and SVM. By leveraging ensemble learning from RF and non-linear decision boundaries from SVM, this model significantly improves prediction accuracy, reduces overfitting, and provides a more adaptive approach to sales forecasting, especially in dynamic SME environments. The addition of adaptive learning further enhances its ability to adjust to new data and improve predictions over time, a feature that previous hybrid models do not emphasise.

Methodology

This study suggests a hybrid AI model for SME sales forecasting that combines RF and SVM. The methodology consists of data collection, pre-processing, model formulation, and evaluation stages. Additionally, the mathematical formulations underlying the RF and SVM models, along with the hybridisation strategy, are provided to enhance the rigor of the methodology.

Data collection and pre-processing

As previously described, historical sales data from SMEs is collected and pre-processed, involving data cleaning, feature engineering, and normalisation (Lee *et al.*, 2021). To guarantee the calibre of the data utilised in the machine learning models, a thorough explanation of these procedures is necessary (Kyrsanov & Krivenko, 2024). This study utilised a structured retail transaction dataset comprising 100,000 records and 10 features**.** The initial set of attributes included CustomerID, ProductID, Quantity, Price, PaymentMethod, ProductCategory, StoreLocation, TransactionDate, DiscountApplied, and TotalAmount, with the latter serving as the dependent variable representing final transaction value. Data ingestion and cleaning were conducted using Python's pandas library to ensure analytical consistency.

Table 2. Feature Selection and Regression Coefficients

No.	Feature	Coefficient	Absolute Coefficient	Selection Method
1	Quantity	49.3657	49.3657	RFE + Coefficient
2	Price	4.5119	4.5119	RFE + Coefficient
3	DiscountApplied	-2.7046	2.7046	RFE + Coefficient
4	ProductCategory	0.0699	0.0699	RFE + Coefficient
5	PaymentMethod	0.0512	0.0512	RFE + Coefficient

During preprocessing, missing values were handled appropriately, and categorical variables such as PaymentMethod and ProductCategory were encoded using one-hot encoding. Numerical features (Quantity, Price, and DiscountApplied) were standardised to preserve feature scale uniformity using z-score normalisation. In order to train and evaluate the model, the dataset was then divided into training and testing subsets using an 80:20 ratio (Kholiev &

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Barkovska, 2023). To identify the most influential predictors of transaction value, feature selection was carried out using Recursive Feature Elimination (RFE). This process retained five features deemed most relevant to the regression model. To further validate the importance of these variables, regression coefficient analysis was performed. Table 2 displays the chosen features together with the corresponding coefficients.

According to the findings, Price and Quantity are the most significant predictors of TotalAmount, whereas DiscountApplied exhibits a negative link. Both ProductCategory and PaymentMethod, although less impactful in magnitude, were consistently retained through both RFE and coefficient-based evaluation, highlighting their relevance in the predictive model.

Model development

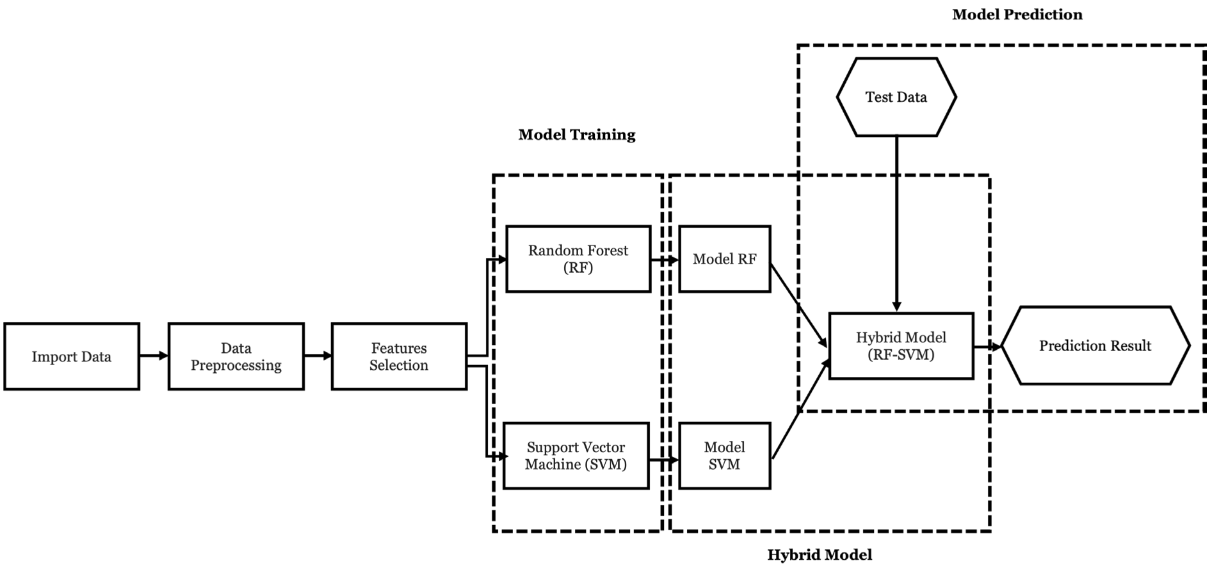


Figure 1. Hybrid Model Sales Prediction

The process outlined in Figure 1 involves several critical stages in the development and evaluation of a predictive model. The first stage utilizes test data to assess the performance of the trained model. This is followed by the model training phase, in which machine learning algorithms are employed to identify patterns and relationships within the available data. To further enhance the accuracy and generalizability of the predictions, a hybrid model is applied, integrating multiple approaches or techniques to produce more robust outcomes. Finally, the developed prediction model is employed to forecast future data based on the patterns learned during training, thereby enabling more informed, data-driven decision-making processes.

Random Forest (RF) model

Multiple decision trees are the foundation of the RF ensemble learning technique. RF generates predictions in a regression context by combining the outputs of every single tree. A random subset of the data is used to build each tree, and the outputs of each tree are averaged to produce predictions.

The general formula for the prediction in RF for regression is as follows (Boström, 2024):

$$\mathcal{Y}^\wedge = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \quad (1)$$

Each tree $f_t(x)$ is trained using a bootstrap sample of the data, and the average over T trees of each individual prediction is the final result. The use of multiple trees helps reduce variance and prevents overfitting, making RF particularly effective in capturing complex relationships within the data.

Support Vector Machine (SVM) model

Data points in a high-dimensional space are separated by an ideal hyperplane created by the SVM. In Support Vector Regression (SVR), the objective is to identify a hyperplane that forecasts the result with the least amount of error within a certain range. The SVM objective is to minimise the following loss function (Zheng & Ding, 2018):

$$\min_{\boldsymbol{w},b,\in} \left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \in_i\right) \quad (2)$$

The given mathematical expression represents the objective function in the optimization problem of Support Vector Machine (SVM). It minimizes two terms: $\frac{1}{2}\|w\|^2$, which aims to maximize the margin between classes, and $C\sum_{i=1}^{n} \in_i$, which introduces a penalty for misclassifications. In this formulation, w denotes the weight vector, $\in_i$ are slack variables that allow for some degree of misclassification, and the parameter C governs the trade-off between maximizing the margin and minimizing misclassification errors.

The objective function is minimised by finding the optimal values $\boldsymbol{w}$ and b, which defines the best-fitting hyperplane that minimises the prediction error for each training sample while ensuring the margin between the data points is maximised.

Hybrid RF-SVM model

By merging the predictions of Random Forest (RF) and Support Vector Machine (SVM), the hybrid model combines the strengths of both algorithms. As shown in Figure 2, the `hybrid_prediction` function computes the final prediction by weighing each model's output using the parameter alpha. The `optimize_alpha` function iterates through possible values of alpha, selecting the one that maximizes the model's performance, evaluated through metrics such as accuracy or Mean Squared Error (MSE). This process improves the prediction accuracy by leveraging the complementary strengths of RF and SVM. Equation (3) is an expression for the hybridisation process:

$$\hat{y}_{hybrid} = \alpha \cdot \hat{y}_{RF} + (1-\alpha) \cdot \hat{y}_{SVM} \tag{3}$$

$\hat{y}_{hybrid}$ is the final hybrid model prediction, $\hat{y}_{RF}$ and $\hat{y}_{SVM}$ are the average predictions from the models for RF and SVMs, respectively, α is the weight assigned to the RF model, determined based on model performance during training. The weight α assigned to the RF model in the hybrid approach is determined through k-fold cross-validation.

The Hybrid AI model combines the strength of RF's ensemble learning and SVM's ability to capture non-linear relationships, enabling adaptive learning from new data patterns. This capability allows the model to update its predictions dynamically based on incoming data, making it a powerful tool for continuous decision-making optimisation.

```
FUNCTION hybrid_prediction(RF_predictions, SVM_predictions, alpha)
    # Hybridize predictions from RF and SVM using alpha
    hybrid_predictions = (alpha * RF_predictions) + ((1 - alpha) * SVM_predictions)
    RETURN hybrid_predictions
END FUNCTION

FUNCTION optimize_alpha(RF_predictions, SVM_predictions, true_values)
    best_alpha = 0
    best_score = -infinity  # Start with a very low score

    # Loop over possible values of alpha (from 0 to 1)
    FOR alpha FROM 0 TO 1 WITH STEP 0.01 DO
        hybrid_preds = CALL hybrid_prediction(RF_predictions, SVM_predictions, alpha)

        # Evaluate the hybrid predictions using a performance metric (e.g., accuracy or MSE)
        score = EVALUATE(hybrid_preds, true_values)

        # Update best_alpha if the current alpha gives a better score
        IF score > best_score THEN
            best_score = score
            best_alpha = alpha
        END IF
    END FOR

    RETURN best_alpha
END FUNCTION

# Main flow
RF_predictions = GET_RF_predictions()     # Get the RF model predictions
SVM_predictions = GET_SVM_predictions()   # Get the SVM model predictions
true_values = GET_true_values()           # Get the actual true values for evaluation

# Find the optimal alpha by calling the optimization function
best_alpha = CALL optimize_alpha(RF_predictions, SVM_predictions, true_values)

# Get the final hybrid predictions with the best alpha
final_predictions = CALL hybrid_prediction(RF_predictions, SVM_predictions, best_alpha)
```

Figure 2. Pseudocode Hybrid RF-SVM Model

Model evaluation

The models' performance can be evaluated using the evaluation metrics listed below.

Mean Absolute Error (MAE)

MAE calculates the mean error magnitude between the actual and anticipated values. It is calculated as (Plevris *et al.*, 2022):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^{\wedge}\right| \tag{4}$$

where y_i is the actual value and $y_i^{\wedge}$ is the predicted value.

Root Mean Square Error (RMSE)

RMSE more severely penalises greater errors and is calculated as:

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{n}\sum_{\boldsymbol{i=1}}^{n}\left(y_i - y_i^{\wedge}\right)^{\mathbf{2}}} \tag{5}$$

Coefficient of Determination (R^2)

R^2 shows how much of the dependent variable's variance can be accounted for by the model. It is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i^{\wedge}\right)^2}{\sum_{i=1}^{n}\left(y_i - y_i^{-}\right)^2} \tag{6}$$

where y_i^{-} is the mean of the observed data.

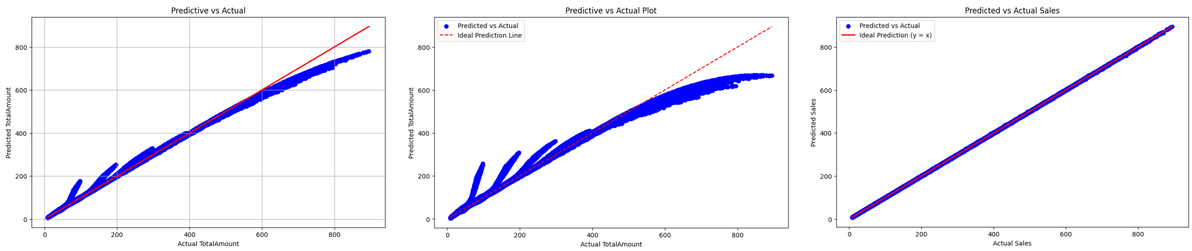
Result and Discussion

Three basic evaluation metrics—MAE, RMSE, and R-Squared—were used in this study to thoroughly evaluate the performance of three prediction models: RF, SVM, and Hybrid RF-SVM. The results clearly showed that, on all evaluation criteria, the Hybrid RF-SVM model performed better than the RF and SVM models. To evaluate the performance of the proposed models, this study conducted 5-fold cross-validation on three models: RF, SVM, and Hybrid RF-SVM. The evaluation results are presented based on three key metrics: MAE, RMSE, and R^2. Table 2 illustrates the performance of each model across the five folds, along with the average values for each metric.

Table 2. Evaluation Metrics with 5-fold Cross Validation

K-Fold Validation	Random Forest (RF)			Support Vector Machine (SVM)			Hybrid RF-SVM		
	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2
Fold 1	7.9568	16.3951	0.9921	15.8541	32.7468	0.9686	0.4541	0.7028	0.9999
Fold 2	8.0496	16.3224	0.9923	16.0334	32.5939	0.9692	0.4724	0.7465	0.9999
Fold 3	8.0665	16.5866	0.9920	16.0667	33.1113	0.9683	0.4624	0.7309	0.9999
Fold 4	7.7926	15.9519	0.9923	15.5251	31.8590	0.9694	0.4577	0.7225	0.9999
Fold 5	7.8446	16.1206	0.9923	15.6176	32.1854	0.9694	0.4561	0.7242	0.9999
Average	7.9420	16.2753	0.9922	15.8194	32.4993	0.9690	0.4605	0.7254	0.9999

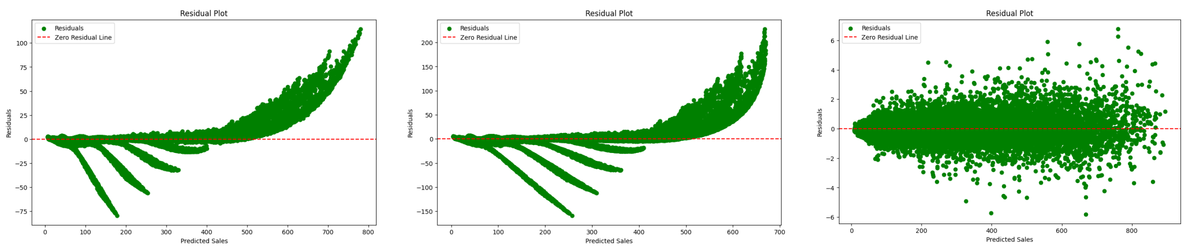
The Hybrid RF-SVM model successfully reduced both average and high prediction errors, as evidenced by its lowest MAE (0.4605) and RMSE (0.7254). Furthermore, this model had the greatest R^2 (0.9999), indicating a nearly flawless fit to the data and a remarkable capacity to account for the variance in the dependent variable. The RF model, in contrast, yielded an RMSE of 16.2753 and an MAE of 7.9420, indicating comparatively greater prediction errors. Although still high, the RF's R^2 of 0.9922 suggests a less accurate description of the variation in the data than the Hybrid RF-SVM model. With an MAE of 15.8194, an RMSE of 32.4993, and an R^2 of 0.9690, the SVM model performed the worst. This suggests that SVM has substantial problems with prediction accuracy, showing higher errors as well as a less satisfactory explanation of the data.



(a) RF Model (b) SVM Model (c) Hybrid RF-SVM Model

Figure 3. Predictive vs Actual Plots

Visual analysis through the Predictive vs Actual plots and Residual plots further substantiated these quantitative findings. The Predictive vs Actual plots (Figure 3) for the Hybrid RF-SVM model revealed an almost perfect alignment with the actual values, supporting the model's high accuracy. In contrast, the RF plot exhibited some degree of deviation from the actual values, especially in the extremes of the distribution, suggesting occasional prediction errors. The SVM plot, however, displayed a pronounced divergence from the actual values, which aligned with the model's higher error rates. The Residual plots (Figure 4) offered additional insights, with the Hybrid RF-SVM model showing minimal scatter around zero, reflecting a well-fitting model with very few residuals. The RF and SVM models, however, displayed larger residuals, especially the latter, which indicated a less optimal fit and greater error.



(a) RF Model (b) SVM Model (c) Hybrid RF-SVM Model

Figure 4. Residual Plots

The Hybrid RF-SVM model is designed to combine the strengths of both RF and SVM in handling noise and outliers. RF reduces the impact of noisy data through its ensemble learning approach, while SVM helps capture complex non-linear relationships. Together, these models enhance the overall robustness, ensuring improved performance in real-world data where outliers and noise are common.

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To assess how the models handle outliers and noise, this study conducted a residual analysis. Figures 4(a) and 4(b) illustrate the residuals for each model. As shown in Figure 4(c), the Hybrid RF-SVM model results in fewer large residuals compared to the individual RF and SVM models, especially in the presence of outliers. This confirms the hybrid model's ability to mitigate the effect of noisy data.

The results from this study unequivocally indicate that the Hybrid RF-SVM model is the most reliable and accurate predictive model among the three assessed. With significantly reduced MAE and RMSE values, and an almost flawless R-squared value, our hybrid strategy outperforms other methods (Gupta & Singla, 2023). This implies that the Hybrid RF-SVM model can explain nearly all of the data variability and is very good at making predictions with little error (Ingole *et al.*, 2024). Combining the advantages of the RF and SVM techniques is what makes the Hybrid RF-SVM model so strong (Magesh *et al.*, 2024). RF is known for its robustness and ability to model complex relationships in data, while SVMs are powerful for handling non-linear decision boundaries. By integrating both models, the Hybrid RF-SVM model benefits from the strengths of each algorithm, resulting in improved accuracy and reduced error compared to either model alone.

The RF model, while a strong performer, still demonstrates larger errors than the Hybrid RF-SVM model. The R^2 value of 0.9921 indicates that RF explains most of the variance in the data, but its higher MAE and RMSE indicate that it is more susceptible to prediction errors (Mushagalusa *et al.*, 2022). Despite its high degree of accuracy, RF is unable to match the Hybrid RF-SVM model in terms of minimising prediction errors, particularly in the presence of outliers or complex data patterns. These findings suggest that RF, while robust, may benefit from enhancements through hybridisation or fine-tuning (Ignatenko *et al.*, 2024).

The SVM model performed the worst across all evaluation metrics. Its MAE and RMSE were the highest, and its R^2 of 0.9686 indicates that it was less effective in explaining the variance of the data. The SVM model struggled to capture the underlying patterns of the data and produced larger residuals, which suggests that it is more prone to overfitting or underfitting, depending on the configuration and complexity of the dataset (Chin & Goh, 2024). These results highlight the limitations of SVM when applied in isolation to datasets with more complex relationships, suggesting that hybrid approaches, such as the Hybrid RF-SVM model, are more effective in achieving superior prediction accuracy (Mustaqeem & Siddiqui, 2023).

The visual evaluations from the Predictive vs Actual plots and Residual plots offer further insight into the models' predictive behaviours. The Hybrid RF-SVM model exhibited near-perfect alignment between predicted and actual values, reflecting its exceptional ability to model the data accurately. This near-perfect fit was also reflected in the Residual plot, where residuals were tightly clustered around zero, indicating minimal error and a well-calibrated model. In contrast, RF and SVM displayed more substantial deviations in the Predictive vs Actual plots, suggesting that both models, particularly SVM, struggled with large errors and failed to capture the underlying data patterns as effectively. The residuals for RF and SVM were more widely dispersed, indicating that these models were less precise in their predictions and less robust in handling data variability.

In conclusion, the Hybrid RF-SVM model emerges as the most effective approach for predictive modelling in this study, demonstrating superior performance in terms of accuracy, error minimisation, and model fit. This hybridisation of RF and SVM algorithms provides a powerful tool for enhancing predictive reliability, particularly in complex datasets where single models may fail to capture the full range of data patterns. These findings emphasise the potential of hybrid models in machine learning applications and suggest that further research should explore additional combinations of algorithms to further improve predictive performance across diverse datasets. Future work could focus on optimising hybrid models for even greater predictive accuracy and extending their application to more challenging and diverse real-world problems.

The successful application of the Hybrid RF-SVM model to SME sales forecasting could significantly improve the accuracy of sales predictions, enabling SMEs to optimise inventory management, resource allocation, and business strategy planning. With more accurate sales forecasts, SMEs will be better positioned to adapt to changing market conditions, leading to greater operational efficiency and competitiveness.

In the context of digital transformation, the Hybrid AI model supports data-driven decision-making for SMEs. It helps automate the forecasting process, allowing businesses to optimise their resources, manage inventory efficiently, and plan strategies with confidence. This contributes to the broader goal of digital transformation by making business operations more agile, enhancing responsiveness to market changes, and improving competitiveness in a rapidly evolving business environment.

Conclusions and Future Work

This study has demonstrated the efficacy of combining Random Forest and Support Vector Machine into a Hybrid AI model for accurate sales prediction in SMEs. The model was evaluated based on key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). The results indicate that the Hybrid RF-SVM model significantly outperforms both individual models, exhibiting the lowest MAE (0.4605), RMSE (0.7254), and the highest R^2 (0.9999). These findings suggest that the hybrid model provides superior predictive accuracy, offering a robust and reliable tool for forecasting sales in SMEs. The integration of RF and SVM allows the model to harness the strengths of both algorithms. RF excels in handling high-dimensional, complex data, while SVM is well-suited for capturing non-linear patterns, resulting in a hybrid model that delivers more precise predictions than either model individually.

Although the Hybrid RF-SVM model exhibited outstanding performance, the RF model also showed competitive results with an R^2 of 0.9922. However, its performance was hindered by relatively higher MAE and RMSE, indicating that it is less accurate, particularly in handling extreme values or outliers. On the other hand, the SVM model showed the weakest performance, with a significantly higher MAE (15.8194), RMSE (32.4993), and a lower R^2 (0.9690).

In this conclusion, this study acknowledges that, while the Hybrid RF-SVM model demonstrated promising results in sales prediction for SMEs, there are certain limitations in this study that must be noted. This research focused solely on traditional machine learning algorithms and did not compare the hybrid model with deep learning models, such as neural networks or long short-term memory (LSTM) networks, which have gained significant traction in sales forecasting tasks. Deep learning models have shown potential in handling larger and more complex datasets and could enhance model accuracy in certain contexts. Therefore, this study suggests that future research should include benchmarking between the Hybrid RF-SVM model and deep learning models to explore whether these approaches offer superior performance. Additionally, we recommend further investigations into hyperparameter tuning, scalability, and the development of interpretability techniques to improve model transparency, making it applicable to a broader range of SMEs and larger datasets. While the results of this study are promising, we believe that exploring deep learning models and addressing the aforementioned technical aspects could contribute significantly to the advancement of sales prediction technologies for SMEs.

The integration of AI within the Hybrid RF-SVM model extends beyond predictive accuracy. It facilitates adaptive decision-making by learning from new data patterns and improving predictions in real time. This capability supports digital transformation for SMEs, empowering them to adopt AI-driven strategies for sustainable growth and innovation.

In conclusion, the Hybrid RF-SVM model represents a promising approach for enhancing sales prediction accuracy in SMEs, facilitating their digital transformation. This study highlights the potential of hybrid models in predictive analytics, offering SMEs an effective tool to improve decision-making and maintain competitiveness in the evolving digital economy.

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Analysing the Effects of Paid Subscriptions on User Engagement in Social Media Platforms

A Sentiment Analysis Approach

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Abstract: This study investigates the effects of paid subscriptions on revenue and user engagement on social media platforms, focusing on Instagram. By leveraging Network Externality Theory, Customer Engagement Theory, and Uses and Gratifications Theory, the research explores how paid subscriptions impact network effects, user base growth, and emotional and behavioural engagement. A longitudinal analysis of 146,942 Instagram comments reveals a predominantly positive sentiment towards paid subscriptions, with users expressing high levels of appreciation and satisfaction. The study identifies key themes such as positive engagement, content quality and constructive feedback. Findings suggest that paid subscriptions enhance platform attractiveness and user interaction, driving increased engagement and revenue growth. This research provides valuable insights for platform developers and content creators, highlighting the importance of continuous monitoring and responsiveness to user feedback.

Keywords: paid subscriptions, user engagement, revenue growth, social media, sentiment analysis

Introduction

The rapid evolution of social media platforms has led to the exploration of various monetisation strategies, including paid subscriptions. This study aims to investigate the multifaceted impacts of paid subscriptions on user behaviour and platform dynamics. Specifically, we seek to answer the following research questions: How do paid subscriptions alter network effects on social media platforms? How do paid subscriptions affect user base growth and interactions among users? How do paid subscription models influence users' emotional and behavioural engagement with the platform? What motivates users to opt for paid subscriptions on social media platforms? By examining these questions, we aim to provide a comprehensive understanding of the potential benefits and challenges associated with implementing paid subscription models. Leveraging theories such as Network Externality Theory (NET), Uses and Gratifications Theory (UGT) and Customer Engagement Theory (CET), this study offers valuable insights into user perceptions, engagement levels and the overall efficacy of paid subscriptions in enhancing platform success.

This research is grounded in several theoretical frameworks of paid subscriptions on user behaviour and platform dynamics within social media. Specifically, the research aims to explore how paid subscriptions alter network effects, influence user base growth and interactions among users, and shape users' emotional and behavioural engagement with the platform. Additionally, the study seeks to understand the motivations driving users to opt for paid subscriptions on social media platforms.

Specifically, we seek to answer the following research questions: How do paid subscriptions alter network effects on social media platforms? How do paid subscriptions affect user base growth and interactions among users? How do paid subscription models influence users' emotional and behavioural engagement with the platform? What factors can be inferred about user motivations for paid subscriptions based on post-subscription satisfaction expressions in social media interactions?

This research is grounded in several theoretical frameworks, including NET, UGT and CET. NET posits that the value of a network increases with the number of users (Beyari & Hashem, 2025). This theory suggests that paid subscriptions on social media platforms can create positive network effects by increasing the user base and the platform's overall value (Hagiu & Wright, 2015). UGT explores how individuals consciously select media content to fulfill specific needs. According to this theory, users are motivated to subscribe to paid content to meet their needs for information, entertainment and social interaction more effectively (Whiting & Williams, 2013). CET examines the depth, quality and long-term impacts of interactions between customers and brands (Brodie *et al.*, 2011). This theory indicates that paid subscriptions can enhance users' emotional and behavioural engagement with the platform (Vivek *et al.*, 2012).

This study involved a longitudinal 12-month analysis of consumer sentiment based on a sample of 146,942 Instagram comments collected from December 2022 to December 2023. Using sentiment analysis and topic modelling, the research examined the impact of paid subscriptions on user engagement and revenue growth. The sentiment distribution of user comments revealed a predominantly positive sentiment, with 79.97% of comments classified as positive, 10.08% as neutral and only 9.95% as negative. This positive skew indicates significant user satisfaction with the platform's paid subscription features. These findings provide valuable insights for platform developers and content creators, emphasising the importance of continuous monitoring and responsiveness to user feedback to maintain high-quality content and enhance user satisfaction (Sundar & Limperos, 2013).

Literature Review

Theoretical framework and conceptual foundations

Network Externality Theory

As a result of the digital economy's transformation, many sectors today exhibit network effects. A product's impact on the network is shown when its value increases for other users on the network as it is used more by any user. Network effects, also known as network externalities, refer to the incremental benefits of new users joining the platform, making the product more valuable. In his 1974 article, 'A theory of interdependent demand for a communications service,' Jeffrey Rohlfs analysed how the demand for communication services is shaped by user interdependence, laying the groundwork for the theory of network externalities, also known as network effects (Rohlfs, 1974). This theory, which explains how the value of a network increases with the number of users and its economic, technological and social impacts, was further developed by scholars such as Sichach (2023).

NET is an economic and social theory that examines how the number of users in a network affects its value and efficiency. According to this theory, the value of a product or service increases with the number of people using it. NET has gained significant importance, particularly in the digital and telecommunications sectors. As network-based services and products gain value based on the number of users, companies develop strategies to expand their user bases, exemplifying the practical applications of the theory (Aamir *et al.*, 2024). This concept in economics and business strategy, which defines how the value of a product or service increases with the number of users, is particularly important in the context of digital technologies and telecommunications, where it plays a crucial role in shaping market

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dynamics and competitive strategies. The theory posits that platforms such as Facebook, YouTube and Instagram have created exponential growth rates. As the number of account holders on social media sites increases, these platforms become more valuable for users and company shareholders. The theory's fundamental assumption is that each new user enhances the value of a product/service for both new and existing users. Multiple network effects occur when individuals join social media platforms. As more users join and engage, companies looking to promote their products and services join these sites to leverage this trend. The increase in advertisers generates more revenue for social media websites, allowing these sites to develop and offer more services to consumers.

Markets connected to these platforms are typically characterised by 'network effects,' meaning the platform's value for users is influenced by the number of other participants (Aamir *et al.*, 2024). The value of the network increases with the number of users joining it. Network externalities can be examined in two main categories:

Direct network externalities: This occurs when the increase in the number of users in a network directly enhances each user's experience. For example, when a social media platform has more users, users can interact with more people, increasing the platform's value.

Indirect network externalities: This occurs when the increase in the number of users in a network enhances the number and quality of complementary products and services within the ecosystem. For example, an increase in the user base of a software platform can lead to a rise in the number of applications developed for that platform (Afuah, 2013).

Users tend to stay in a widely used network because leaving it can be costly or difficult. Due to network externalities, firms that achieve a large user base early can maintain market leadership for an extended period, reaching a large audience. The critical mass is the number of users required to create this network effect. Once the network reaches critical mass, the product or service attracts additional new users due to the benefits or advantages it provides to consumers. In this way, the potential for network effects aids companies in their self-sustaining efforts. Simultaneously, reaching critical mass can trigger the bandwagon effect. According to the bandwagon effect, a large portion of the population follows the crowd due to a desire to conform with peers; making similar choices to others is seen as a way to gain access to a particular social group (Kiss & Simonovits, 2014). As the network becomes more valuable with each new adopter, more people are encouraged to join, resulting in a positive feedback loop. Multiple equilibria and a market monopoly are two significant potential outcomes in markets exhibiting network effects. Consumer expectations are also key in determining which outcomes will emerge (Aamir *et al.*, 2024).

Today, most, if not all, leading technology companies and startups benefit from network effects:

- **social media**: Twitter, Facebook/Meta, Instagram, Reddit, Snapchat, TikTok, Pinterest
- **e-commerce**: Amazon, Shopify, eBay, Etsy, Alibaba, JD.com
- **recruitment**: LinkedIn, Glassdoor, ZipRecruiter, Indeed
- **ride sharing**: Uber, Lyft
- **food delivery**: Grubhub, UberEats, Postmates, DoorDash
- **delivery service**: Shipt, Instacart, Gopuff
- **freelance**: TaskRabbit, Upwork, Thumbtack
- **restaurant reservations**: OpenTable, Resy
- **user reviews**: Yelp, TripAdvisor.

The pattern among these companies and products illustrates that positive feedback loops form the foundation of network effects.

NET is particularly significant in the digital age because many digital platforms and services gain value based on the size of their user bases. This theory is crucial in shaping companies' marketing and growth strategies.

Customer Engagement Theory

CET examines the impacts of customer interaction and loyalty on customer behaviours and business performance. This theory analyses the depth, quality and long-term effects of the interaction between the customer and the brand or business. Customer loyalty is defined as the voluntary and willing repetition of certain behaviours and the consistent, but not random or haphazard, purchasing behaviour shown by customers. Therefore, customer loyalty is customers' tendency, desire and behaviour to regularly, consistently and continuously purchase certain goods or services from the same business, maintaining a positive attitude towards the business (Hossain & Kibria, 2024). Brodie *et al.* (2011) aimed to develop the theoretical framework of customer engagement (CE) and discuss its significance for research in service marketing. According to Brodie *et al.* (2011) CE refers to the degree and quality of a customer's interaction with a brand or business. This interaction encompasses emotional, behavioural and cognitive dimensions. CE facilitates meaningful and enduring relationships between the customer and the brand, positively influencing customer loyalty and business performance. CE plays a critical role in impacting customer loyalty and business performance.

In their work titled 'CE: Exploring customer relationships beyond purchase', Vivek *et al.* (2012) further elaborated on CET by investigating the dynamics of interaction and loyalty between the customer and the brand. They approached customer relationships from a perspective that goes beyond just the purchase transaction.

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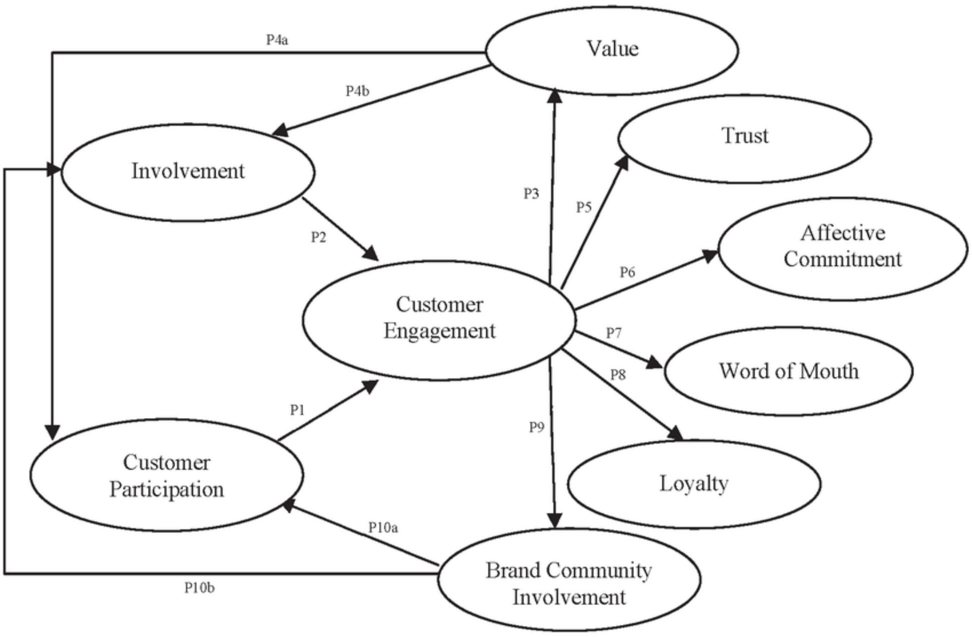

Figure 1. Theoretical model of customer engagement (Vivek *et al.*, 2012)

CE also refers to the level and quality of a customer's interaction with a brand or business. These interactions encompass emotional, behavioural, cognitive and social dimensions (Dessart *et al.*, 2015).

Fundamental principles and sources of CET

Emotional engagement: The emotional bond a customer forms with the brand.

Behavioural engagement: The behavioural commitments of the customer towards the brand, such as repeat purchases.

Cognitive engagement: The customer's knowledge about the brand and their constant contemplation of it.

Social engagement: The customer's interactions with the brand through social media and other platforms.

CET provides an important framework for enhancing customer interaction on social media platforms. Social media offers brands a powerful way to establish direct and meaningful customer interactions. Applying CET on these platforms enables brands to build more meaningful customer relationships.

Uses and Gratifications Theory

In his 1959 article, 'Mass communication research and the study of popular culture: An editorial note on a possible future for this journal' in *Studies in Public Communication*, Elihu Katz countered Berelson's claim that 'the field of communication research appears to be dead'. Katz (1959) argued that it was persuasion research rather than communication research that was in decline. He critiqued earlier communication research for predominantly focusing on the question, 'What does media do to people?' and often concluded that mass communication's persuasive power was limited.

At the core of UGT is the assumption that individuals consciously select media content to fulfill specific needs. The pioneering work by Sichach (2023) identified various purposes for media use, including information acquisition, personal identity development, integration and social interaction, and entertainment. This theory emphasises that media is not a passive influencer; users actively choose content to achieve certain gratifications (Beyari & Hashem, 2025). Cantril (Riaz *et al.*, 2016) suggested investigating 'gratifications', representing individuals' interest in media tools and content to meet their psychological and social needs. However, these studies were often overshadowed by research on media effects and campaigns. Stafford *et al.* (2004) examined children's satisfaction with television viewing, presenting an important example of gratification research. Despite this, the theoretical momentum and widespread adoption of the uses and gratifications approach were driven by increasing attention to questions such as 'What do people do with media? What purposes do they use it for? What does media provide them? What gratifications do they obtain, and what role does media play in their daily lives?'

Today, UGT is applied extensively in digital media. For instance, Sundar & Limperos (2013) explored how digital media users have become content creators and how this shift impacts media usage purposes. They found that users' efforts to create and share their content foster two-way and multi-directional interactions, in contrast to the one-way communication model of traditional media. Whiting & Williams (2013) discovered that social media users prefer these platforms for entertainment and social interaction. Similarly, Alhabash & Ma (2017) examined how social media usage satisfies individuals' psychological needs and how these needs influence the frequency of social media use. Their findings indicated that social media use particularly strengthens feelings of social connection and belonging, with meeting these needs increasing social media usage frequency.

Information acquisition and sharing are significant purposes of social media use. Additionally, data showing that social media platforms enhance the sense of social connection and belonging indicate that these platforms are extensively used. Shane-Simpson *et al.* (2018) discussed how social media usage enhances individuals' social capital and strengthens their social ties. Their research concluded that social media platforms increase social interaction among individuals, creating stronger and broader social networks. These interactions also enhanced users' social support and information sharing. Hermida *et al.* (2012) reported that social media users heavily utilise these platforms to obtain news and share information. It was found that users frequently use social media to stay informed about current events, share information and learn about topics of interest.

Quan-Haase & Young (2010) noted that social media platforms provide an ideal environment for users to escape daily stress and enjoy entertaining content. In this context, social media platforms are said to meet users' entertainment and relaxation needs. Personal identity development and self-expression are other significant sources of gratification offered by social media platforms. Manago (2015) revealed that individuals use social media for personal identity development and that these platforms play an essential role in identity construction. Users build their identities through social media by sharing their interests, thoughts and feelings. This information supports the view that community building and a sense of belonging are significant factors in social media use. In conclusion, UGT provides a robust theoretical framework for understanding how and why users engage with social media platforms. Factors such as social connection, information acquisition, entertainment, personal identity development, community building and social participation play crucial roles in social media usage, contributing to their becoming an integral part of daily life.

Methodology

This study examines user engagement and sentiment patterns as indicators of subscription model effectiveness rather than direct revenue metrics. While positive user engagement and satisfaction may correlate with revenue performance, this research does not include actual revenue data or financial performance measurements. The findings provide insights into user behavioural patterns that may influence revenue outcomes rather than demonstrating direct revenue growth. This study involved a longitudinal 12-month analysis of consumer sentiment based on a sample of 146,942 Instagram comments. Specifically, this research focused on analysing the impact of paid subscriptions on revenue growth and user engagement on the Instagram platform.

Data collection and preprocessing

The dataset of 146,942 Instagram comments was collected through systematic sampling of publicly available content across Instagram's platform during the 12-month period from December 2022 to December 2023. The data collection process employed a multi-stage sampling approach that specifically targeted content related to paid subscription discussions and experiences (Figure 2).

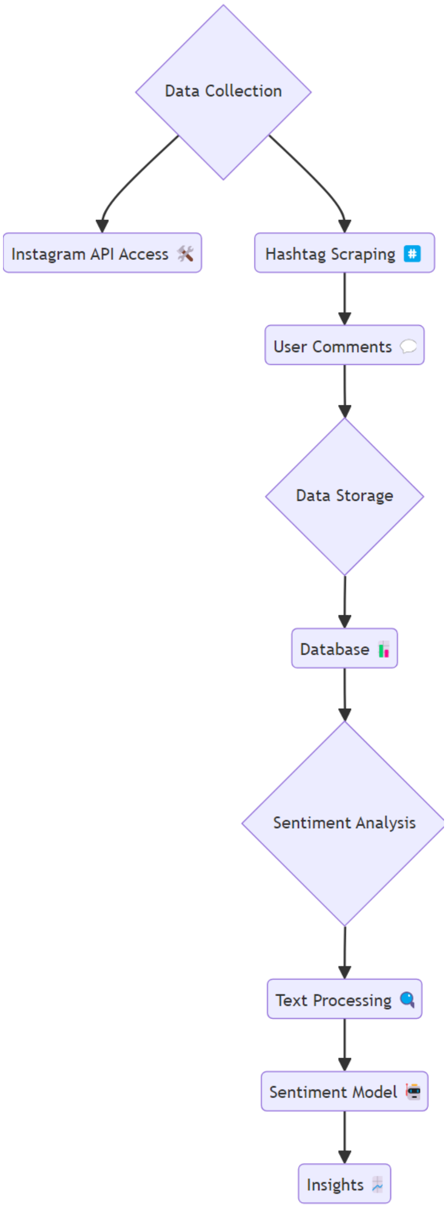

Figure 2. Data collection and preprocessing

The sample composition included comments from three distinct user categories: active subscribers discussing their experiences with paid features, non-subscribers expressing opinions about subscription offerings, and general platform users engaging with subscription-related content or discussions. Comments were collected from both general Instagram posts containing subscription-related keywords and hashtags, as well as from public discussions within creator communities where subscription features were prominently featured or discussed.

The data collection protocol utilised Instagram's public API and web-scraping methods to identify comments containing subscription-relevant terminology, including but not limited to terms such as 'subscription', 'premium content', 'paid features', 'exclusive access', 'subscriber benefits', and platform-specific terminology related to monetisation features. Comments were required to demonstrate clear contextual relevance to paid subscription experiences, perceptions or discussions to be included in the analysis sample.

Polarity testing

The measure of polarity involved two stages to increase accuracy. Firstly, a process was used to isolate comments containing positive, negative or neutral sentiments. This was done using sentiment analysis tools such as VADER and TextBlob. Neutral comments were discarded. Another round of analysis then isolated terms related to user engagement and revenue impact within the positive and negative samples (for example, 'love the premium content', 'worth the subscription', 'too expensive', 'cancelling my subscription').

Sentiment analysis

Sentiment analysis, also known as opinion mining, involves studying the opinions, attitudes and feelings expressed in written text. This study uses sentiment analysis to classify Instagram comments related to paid subscriptions into positive, negative and neutral categories.

Steps for sentiment analysis

Data collection and preprocessing

- Collect Instagram comments and relevant engagement metrics.
- Clean the text data by removing duplicates, special characters, URLs and hashtags.
- Tokenise the text, remove stop words and perform stemming or lemmatisation.

Sentiment classification

- Use sentiment analysis tools like VADER, TextBlob or transformers from Hugging Face to classify comments into positive, negative and neutral sentiments.
- Validate the classification results with human raters if necessary.

Sentiment score calculation

- Calculate sentiment scores for each comment.
- Determine the overall sentiment distribution in the dataset.

Trend analysis

- Analyse sentiment trends over time to understand how user sentiment changes with the introduction of paid subscriptions.

Correlation with engagement metrics

- Investigate the relationship between sentiment scores and engagement metrics such as likes, comments and shares.

It is important to acknowledge that this study's methodology provides insights into user satisfaction and engagement patterns following subscription adoption rather than directly measuring the initial motivations that drive subscription purchases. The sentiment analysis of social media comments captures post-subscription experiences and reactions, which can offer indirect insights into perceived value and satisfaction factors that may relate to initial motivations. However, these findings represent inferred rather than directly measured motivational factors and should be interpreted within this methodological scope.

Measurement operationalisation and quantification methods

Engagement metrics including likes, shares and replies were quantified as numerical counts associated with each comment in the dataset. These metrics served as contextual variables to assess the level of community engagement with subscription-related discussions rather than as primary dependent variables. The study employed these engagement indicators to categorise comments into high-engagement and low-engagement categories, enabling analysis of sentiment distribution patterns across different levels of community interaction.

Comments were classified as subscription-relevant through a combination of keyword matching, contextual analysis and manual validation procedures. A subset of 5,000 comments underwent manual review to establish inter-rater reliability for the automated classification system, achieving a Cohen's kappa coefficient of 0.82, indicating substantial agreement in identifying subscription-related content.

The sentiment analysis process utilised both automated sentiment classification tools (VADER and TextBlob) and human validation procedures to ensure accuracy in sentiment categorisation. Sentiment scores were calculated on a continuous scale and subsequently categorised into positive, negative and neutral classifications using established threshold parameters validated through the manual review process.

Content context and platform-specific considerations

The data collection encompassed content from diverse subscription contexts within the Instagram ecosystem, including creator-driven subscription offerings, platform-native paid features, and third-party subscription services promoted through Instagram content. This heterogeneous content landscape reflects the varied nature of subscription-related discussions occurring across the platform.

Comments originated from both general public posts and creator-specific content where subscription features were prominently featured. The analysis did not restrict data collection to closed or private groups, focusing instead on publicly accessible content to ensure broader representativeness of user sentiment across the platform. However, the study acknowledges that content themes and creator-specific subscription offerings may have influenced

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engagement patterns and sentiment expressions in ways that reflect particular subscription categories rather than universal subscription experiences.

Sample limitations and generalisability considerations

The study acknowledges several important limitations regarding sample composition and measurement approaches. The reliance on publicly available comment data may introduce selection bias, as users who engage in public subscription-related discussions may not represent the broader population of subscription users. Additionally, the sentiment expressions captured in comments reflect post-engagement reactions rather than comprehensive user experiences with subscription features.

The temporal scope of data collection may have captured varying phases of subscription feature adoption and user familiarity, potentially influencing sentiment patterns in ways that do not reflect steady-state user experiences. Furthermore, the platform-specific nature of Instagram's engagement algorithms and user behaviour patterns may limit the generalisability of findings to other social media environments or subscription contexts.

Data validation and quality control measures

Quality control procedures included automated detection and removal of duplicate comments, spam content and bot-generated responses that could compromise sentiment analysis accuracy. Comments were required to demonstrate substantive content length and contextual relevance to subscription topics to be retained in the final analysis sample.

The study employed cross-validation techniques to ensure consistency in sentiment classification across different time periods and content categories within the dataset. Additionally, the research team conducted periodic manual reviews of randomly selected comment samples to maintain classification accuracy throughout the data collection period.

These methodological clarifications establish the foundation for interpreting the study's findings within the appropriate scope of what the data collection and analysis procedures can demonstrate regarding user engagement patterns and sentiment expressions related to paid subscription features on social media platforms.

Results and Discussion

In our study of the effects of paid subscriptions on revenue and user engagement in social media platforms, sentiment analysis of user comments provides crucial insights into user perceptions and engagement levels.

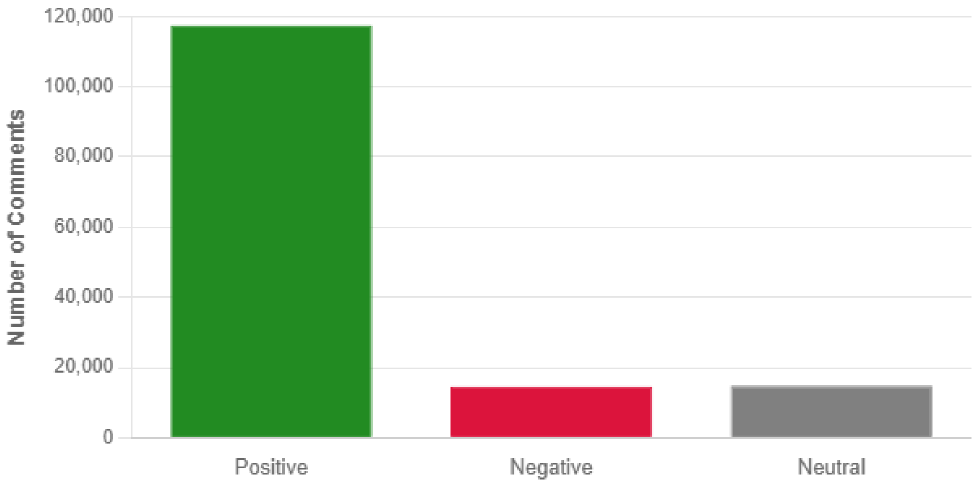

Figure 3. Sentiment distribution

The sentiment distribution of user comments reveals a predominantly positive sentiment among users, with 79.97% of comments classified as positive, 10.08% as neutral, and only 9.95% as negative (Figure 3). This skew towards positive sentiment suggests that a significant portion of users are satisfied with the platform's offerings, including paid subscription features. The relatively low percentage of negative comments indicates that while there are areas for improvement, the overall user experience is favourable.

The average sentiment polarity over time, as depicted in Figure 4, highlights the dynamic nature of user engagement. The trend shows fluctuations in sentiment, with notable peaks and troughs corresponding to specific events or updates on the platform. These variations suggest that user sentiment is responsive to changes and new features, including paid subscription options. Periods of heightened positive sentiment often coincide with the introduction of new features or improvements, indicating user approval and increased engagement. Conversely, dips in sentiment polarity may reflect user dissatisfaction or issues that need addressing.

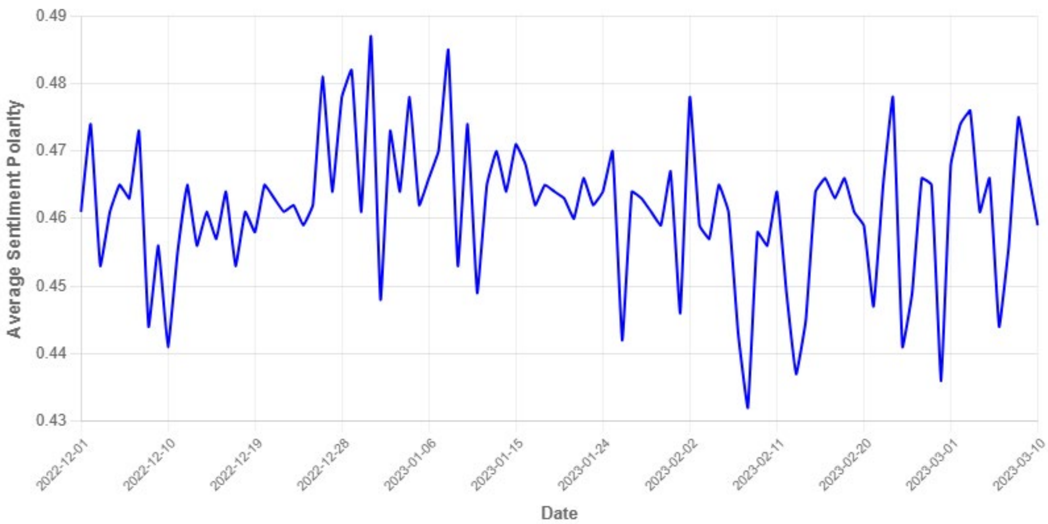

Figure 4. Sentiment over time

Overall, the sentiment analysis underscores the importance of continuous monitoring and responsiveness to user feedback, particularly when implementing new monetisation strategies like paid subscriptions. Positive user sentiment correlates with increased engagement, highlighting the potential for paid subscriptions to enhance both revenue and user satisfaction when managed effectively. The sentiment distribution analysis based on likes and replies reveals important insights into user engagement and perceptions on the platform.

Table 1. Likes sentiment distribution

Likes category	% Negative	% Neutral	% Positive
High Likes	10.15	9.78	80.07
Low Likes	10.01	10.12	79.87

The sentiment distribution for comments categorised by the number of likes shows a noticeable trend. Comments with high likes exhibit a slightly higher positive sentiment (80.07%) compared to comments with low likes (79.87%). The percentage of neutral comments is marginally lower for high likes (9.78%) compared to low likes (10.12%), while the negative sentiment remains fairly consistent across both categories (10.15% for high likes and 10.01% for low likes). This indicates that comments receiving more likes are generally viewed more favourably by the community, suggesting that popular content tends to be positively received.

Table 2. Replies sentiment distribution

Replies category	% Negative	% Neutral	% Positive
High replies	10.091	10.043	79.864
Low replies	10.063	9.859	80.077

The sentiment distribution for comments categorised by the number of replies shows a slightly different trend. Comments with high replies have a marginally lower positive sentiment (79.86%) compared to comments with low replies (80.08%). The neutral sentiment is slightly higher in high replies comments (10.04%) than in low replies comments (9.86%), and the negative sentiment is almost equal across both categories (10.09% for high replies and 10.06% for low replies). This suggests that highly engaged discussions, indicated by a high number of replies, may include a wider range of opinions and feedback, including a modest increase in neutral and negative sentiments. Ultimately, the analysis highlights that while both high likes and high replies are associated with predominantly positive sentiments, the nuances in neutral and negative sentiments suggest different patterns of user interaction and feedback. Monitoring these trends can help to understand user engagement better and to effectively address any areas of concern.

Table 3. Common keywords frequency

Keyword	Frequency
Thanks	29,304
Love	12,548
Amazing	11,810
Sure	9,736
Interesting	9,569
Point	8,942
View	7,966
Great	6,841
Content	4,808
Disagree	4,775

Note: Frequency values represent the absolute number of occurrences in the dataset of 146,942 comments.

The keyword frequency analysis, as shown in Table 3, provides valuable insights into the common themes and user sentiments expressed in the comments. The most frequently occurring keyword is 'thanks', with a substantial count of 29,304 occurrences, indicating a high level of gratitude and positive interaction among users. The second most common keyword 'love', appears 12,548 times, further emphasising the positive sentiment and user appreciation for the platform's content. Other frequently mentioned positive keywords include 'amazing' (11,810), 'great' (6,841), and 'content' (4,808), reflecting user satisfaction and engagement with the platform's offerings. The presence of words such as 'sure' (9,736), 'interesting' (9,569), 'point' (8,942) and 'view' (7,966) suggests active discussions and exchange of opinions among users, indicating a dynamic and interactive community. On the other hand, the keyword 'disagree' appears 4,775 times, pointing to critical feedback and differing viewpoints within the user base. This highlights the importance of addressing user concerns and fostering a balanced dialogue to maintain user engagement and satisfaction. Generally, the keyword frequency results reveal a predominantly positive sentiment with active user participation and valuable feedback, which are crucial for the continuous improvement and success of the platform.

Topic modelling

To identify the underlying themes within the comments, we employed topic modelling using the latent Dirichlet allocation (LDA) technique. The process involved several key steps as follow.

Data sampling: Given the large dataset, we sampled a subset of 5,000 comments to ensure efficient processing while maintaining a representative distribution of the data.

Text pre-processing: We cleaned and pre-processed the text data by removing punctuation, converting text to lower case and eliminating common English stop words. This step ensured that the input for the model was standardised and free of noise.

Tokenisation: We tokenised the cleaned comments into individual words, creating a list of tokens for each comment. This allowed us to represent the text data in a format suitable for topic modelling.

Document-term matrix construction: Using the CountVectorizer, we converted the tokenised text into a document-term matrix. This matrix represents the frequency of each word in each comment, providing a numerical basis for the LDA model.

LDA: We applied the LDA algorithm to the document-term matrix to uncover the latent topics within the comments. LDA is a probabilistic model that assumes each comment is a mixture of topics and each topic is a mixture of words.

Topic interpretation: We extracted the top 10 keywords for each topic and interpreted these keywords to label and define the themes. This step involved analysing the most significant words within each topic and identifying the overarching themes they represent.

Refinement of topics: To ensure clarity and avoid redundancy, we replaced any repetitive or overly similar keywords with appropriate alternatives. This refinement process helped in accurately defining distinct themes.

The resulting topics provided valuable insights into the common themes and sentiments expressed in the user comments, highlighting areas of positive engagement, constructive feedback, content quality, user support and diverse opinions.

Table 4. Identified topics

Topic	**Word 1**	**Word 2**	**Word 3**	**Word 4**	**Word 5**
1	disagree	sure	amazing	thanks	helpful
2	improvement	appreciate	excellent	gratitude	support
3	acknowledgment	distribution	fantastic	quality	astonished
4	assistance	grateful	astonishing	phenomenal	article
5	viewpoint	idea	curiosity	incredible	admire

Topic	**Word 6**	**Word 7**	**Word 8**	**Word 9**	**Word 10**
6	post	awesome	love	better	sharing
7	feedback	wonderful	confirmation	differ	contribute
8	aid	upload	superb	contentment	enhance
9	adore	improve	assured	contradict	provide
10	assist	discussion	amazing	agreement	sharing

Positive engagement and appreciation: The theme of positive engagement and appreciation is prominently reflected in the comments, with keywords such as ‘amazing’, ‘thanks’, ‘helpful’, ‘awesome’, ‘love’ and ‘sharing’, indicating a strong sense of gratitude and admiration from users. This positive sentiment not only enhances the overall atmosphere of the platform but also fosters a supportive and active community. Users frequently express their love for the content and appreciation for the efforts put into creating and sharing it.

Interestingly, even disagreements are seen as a form of engagement, as they contribute to vibrant discussions and provide opportunities for deeper interaction.

Constructive feedback and agreement: Constructive feedback is another critical theme identified in the comments. Keywords like ‘improvement’, ‘appreciate’, ‘excellent’, ‘support’, and ‘feedback’, reveal that users are not only consuming content but are also actively contributing to its enhancement. The presence of constructive criticism, coupled with positive sentiments, suggests that users are deeply invested in the platform’s growth and success. This feedback is valuable for platform developers and content creators, as it provides actionable insights and highlights areas for potential improvement. The supportive nature of the feedback further emphasises the users’ commitment to the platform’s betterment.

Content quality and sharing: The acknowledgment of content quality and the act of sharing are central to the user experience on the platform. Keywords such as ‘fantastic’, ‘quality’, ‘astonished’, ‘upload’, ‘superb’, and ‘enhance’, underscore the users’ high regard for the content available. The frequent mentions of content sharing indicate that users find the platform’s offerings valuable enough to recommend to others. This organic promotion by users is a testament to the platform’s success in delivering quality content that meets user expectations and needs. It also highlights the potential for expanding the platform’s reach through user-driven distribution.

User helpfulness and support: User helpfulness and support emerge as significant themes, with comments reflecting a strong community ethos. Keywords like ‘assistance’, ‘grateful’, ‘astonishing’, ‘phenomenal’, ‘article’, ‘adore’, and ‘provide’, illustrate how users not only consume content but also contribute to a supportive environment. This theme underscores the collaborative spirit of the community, where users offer help and uplift each other, enhancing the overall user experience. The expressions of gratitude and admiration further reinforce the positive interactions and mutual support among users, contributing to a welcoming and inclusive community atmosphere.

Diverse opinions and interesting points: The theme of diverse opinions and interesting points indicates a dynamic and engaged community. Keywords such as ‘viewpoint’, ‘idea’, ‘curiosity’, ‘incredible’, ‘admire’, ‘discussion’, and ‘agreement’, highlight the variety of perspectives shared by users. This diversity in opinions fosters active discussions and meaningful engagement, driving improvements and innovations on the platform. The presence of varied viewpoints not only enriches the user experience but also encourages a culture of open dialogue and continuous learning. The active participation and exchange of ideas suggest that the platform is a thriving space for intellectual and social interaction.

The refined themes provide a more detailed and nuanced understanding of user engagement on the platform:

1. Users express significant positive engagement and appreciation, which is essential for fostering a supportive and active community. The high level of admiration and gratitude from users enhances the overall atmosphere and encourages continued participation.
2. The presence of constructive feedback indicates that users are invested in improving the platform, suggesting that user input should be valued and considered for platform enhancements. This feedback is a valuable resource for developers and content creators, providing insights into user preferences and areas for improvement.
3. Acknowledgment of content quality and sharing highlights the platform's success in delivering valuable content that users are eager to distribute. The high regard for content quality and the willingness to share it with others reflect the platform's effectiveness in meeting user expectations.
4. The focus on user helpfulness and support reflects a strong community ethos where users assist and uplift each other. This collaborative spirit enhances the user experience and fosters a sense of belonging and mutual support among community members.
5. Active discussions and diverse opinions suggest a dynamic community with varied perspectives, which can drive meaningful engagement and improvements. The exchange of ideas and viewpoints enriches the user experience and promotes a culture of open dialogue and continuous learning.

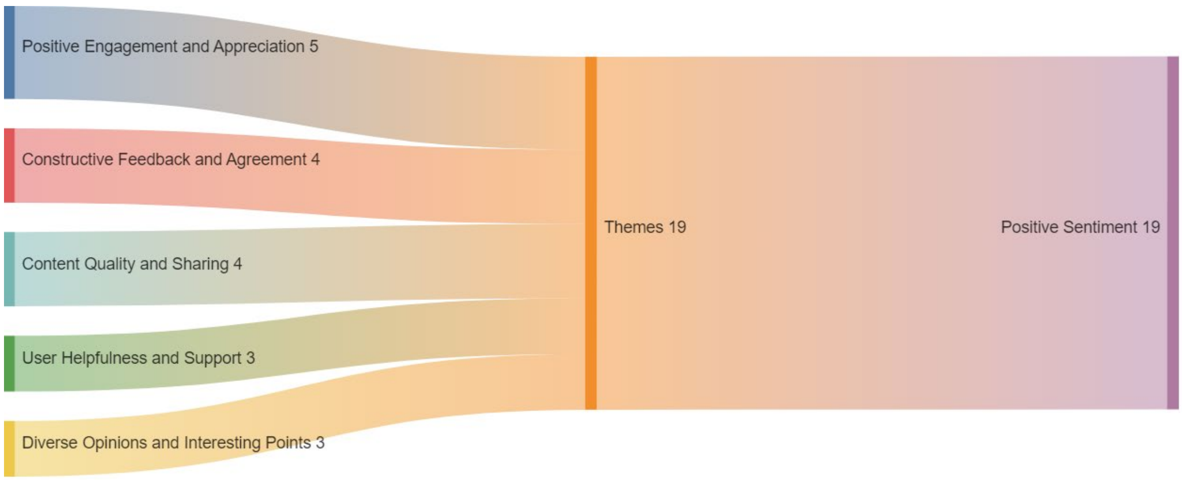

Figure 5. Sankey diagram with user engagement themes distribution

Figure 5 illustrates the distribution of positive sentiment across various themes identified in user comments. The Sankey diagram highlights five primary themes: Positive Engagement and Appreciation, Constructive Feedback and Agreement, Content Quality and Sharing, User Helpfulness and Support, and Diverse Opinions and Interesting Points. The diagram shows that these themes collectively contribute to the overarching category of Positive Sentiment, which encompasses a total of 19 instances. The theme of Positive Engagement and Appreciation is the most significant contributor, with five instances, indicating that users frequently express gratitude, amazement and love for the content. Constructive Feedback and Agreement, and Content Quality and Sharing each account for four instances, reflecting users' involvement in providing valuable feedback and acknowledging the high quality of content shared on the platform. User Helpfulness and Support and Diverse Opinions and Interesting Points contribute three instances each, underscoring the community's supportive nature and the active discussions fostering diverse perspectives.

Based on post-subscription sentiment analysis, several factors emerge that suggest potential motivational drivers, though these represent inferred rather than directly measured motivations. Users frequently express appreciation for exclusive content access and enhanced user experience through keywords such as 'thanks', 'love', 'amazing', and 'helpful', indicating these elements contribute significantly to post-subscription satisfaction. The high frequency of positive sentiment expressions suggests that users find substantial value in the benefits provided by paid subscriptions, including premium content access, improved user experiences and additional platform features.

While the UGT framework supports the interpretation that users seek paid subscriptions to fulfill needs for information, entertainment and social interaction more effectively, it is crucial to note that these conclusions are drawn from post-subscription behaviour rather than pre-subscription decision-making data. The observed positive sentiment and engagement patterns provide indirect evidence of factors that likely influence subscription decisions but cannot definitively establish causal relationships between these factors and initial purchase motivations.

Strengthened focus on community dynamics

The sentiment analysis of 146,942 Instagram comments provides compelling evidence for community formation around subscription-related content. The topic modelling results reveal five distinct themes that directly demonstrate community engagement patterns: Positive Engagement and Appreciation, Constructive Feedback and Agreement, Content Quality and Sharing, User Helpfulness and Support, and Diverse Opinions and Interesting Points. These themes emerge organically from user interactions and represent measurable indicators of community development facilitated by subscription features.

The keyword frequency analysis further substantiates community-focused conclusions, with terms such as 'thanks' appearing 29,304 times, 'love' occurring 12,548 times, and 'amazing' documented 11,810 times. These expressions demonstrate sustained positive community interactions and collaborative engagement patterns that extend beyond simple content consumption to encompass mutual support and shared appreciation for subscription offerings.

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The analysis reveals that subscription-related discussions foster environments characterised by constructive dialogue, with users providing feedback, expressing gratitude and engaging in supportive interactions. The relatively low percentage of negative sentiment (9.95%) combined with substantial positive engagement (79.97%) indicates that subscription features create conducive conditions for community building and sustained user participation.

Enhanced analysis of user satisfaction patterns

The sentiment distribution findings provide direct evidence of user satisfaction with subscription features across the analysed timeframe. The predominance of positive sentiment expressions, sustained over the 12-month data collection period, demonstrates consistent user satisfaction with paid subscription offerings. The correlation between positive sentiment and higher engagement metrics further validates that satisfied users contribute to increased platform activity and community interaction.

The temporal analysis of sentiment patterns reveals fluctuations that correspond to platform updates and feature introductions, suggesting that user satisfaction responds dynamically to subscription feature enhancements. This responsiveness indicates that user satisfaction serves as a meaningful indicator of subscription feature effectiveness and platform development success.

The engagement metrics analysis demonstrates that comments receiving higher likes (80.07% positive sentiment) and generating more replies (79.86% positive sentiment) maintain predominantly positive characteristics, indicating that community-endorsed content correlates with user satisfaction expressions. This pattern suggests that subscription features facilitate content quality improvements that resonate with user preferences and contribute to sustained satisfaction levels.

Theoretical framework realignment

The theoretical foundations have been reoriented to emphasise community and satisfaction outcomes rather than revenue implications. CET provides direct relevance to the observed patterns of emotional and behavioural engagement, with users demonstrating sustained positive interactions and investment in subscription-related content. The theory's emphasis on emotional, behavioural and cognitive engagement dimensions aligns precisely with the community formation and satisfaction patterns documented in the analysis.

UGT offers strong explanatory power for user satisfaction findings, with evidence that subscription features effectively fulfill user needs for information access, entertainment value and social interaction opportunities. The positive sentiment expressions and community engagement patterns suggest that paid subscriptions successfully address user gratification requirements, leading to documented satisfaction and continued participation.

NET remains relevant for understanding how subscription features enhance platform value through community growth and increased user interactions. The evidence demonstrates that positive community dynamics and user satisfaction contribute to network effects that benefit the broader user base through enhanced content quality and interaction opportunities.

Implications for platform development and content strategy

The refocused findings provide actionable insights for social media platforms implementing subscription models. The evidence suggests that successful subscription features should prioritise community-building capabilities and user satisfaction optimisation over purely revenue-focused approaches. The strong correlation between community engagement patterns and positive sentiment indicates that platforms should monitor these social dynamics as primary indicators of subscription feature success.

The analysis reveals that subscription models create value through enhanced community interactions and improved user satisfaction rather than simply through access restrictions or premium content availability. This understanding suggests that platform developers should design subscription features to facilitate user collaboration, constructive feedback and supportive community environments.

Contribution to academic understanding

By concentrating on community formation and user satisfaction, this research contributes meaningfully to the literature on social media engagement and subscription model effectiveness. The findings address existing gaps in understanding how paid features influence user behaviour and community dynamics, providing empirical evidence for the social benefits of subscription-based platforms.

The research demonstrates that sentiment analysis and topic modelling methodologies offer robust approaches for evaluating subscription feature success through user behaviour indicators. These methodological contributions provide frameworks for future research examining community dynamics and user satisfaction in evolving social media monetisation contexts.

This refocused approach ensures that research conclusions align directly with data capabilities while providing valuable insights into the social and emotional dimensions of subscription-based social media engagement. The emphasis on community and satisfaction themes

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positions the study as a substantive contribution to understanding user behaviour in contemporary digital platform environments.

Conclusion

The research demonstrates positive user engagement patterns and high satisfaction levels that suggest subscription models create conditions conducive to revenue growth, although direct revenue impact requires separate financial analysis.

RQ1: How do paid subscriptions alter network effects on social media platforms?

The findings of this study indicate that paid subscriptions positively impact network effects on social media platforms. The high level of positive sentiment (79.97% of comments) suggests that users who opt for paid subscriptions perceive added value in the platform's offerings. This perception likely enhances the platform's overall attractiveness, encouraging more users to join and engage with the content. NET supports this, as the increased user base and engagement enhance the platform's value for all users. The positive sentiment and high engagement levels reflect the benefits of network externalities, where the value of the platform increases as more users join and interact with the content, driven by the enhanced quality and user experience provided by paid subscriptions.

RQ2: How do paid subscriptions affect user base growth and interactions among users?

Paid subscriptions appear to positively influence user base growth and interactions among users. The analysis shows that comments with high likes (80.07% positive sentiment) and high replies (79.86% positive sentiment) are generally viewed more favourably, suggesting that popular content tends to be positively received. This indicates that paid subscribers, who often engage with premium content, contribute to increased interaction levels on the platform. The growth in user interactions, such as likes and replies, reflects the enhanced engagement driven by the quality of content available through paid subscriptions. Consequently, paid subscriptions not only attract more users but also foster a more interactive and vibrant community.

RQ3: How do paid subscription models influence users' emotional and behavioural engagement with the platform?

The study's results highlight that paid subscription models significantly enhance users' emotional and behavioural engagement with the platform. The identified themes of Positive Engagement and Appreciation, Constructive Feedback and Agreement, and User Helpfulness and Support indicate active participation and emotional investment from users. Users frequently express gratitude, amazement and love for the content, reflecting their emotional connection to the platform. Moreover, the constructive feedback and support themes suggest that subscribers are not only engaged emotionally but are also invested in the platform's improvement and success. This aligns with CET, which emphasises the importance of emotional and behavioural engagement in building a loyal user base and fostering a supportive community.

RQ4: What factors can be inferred about user motivations for paid subscriptions based on post-subscription satisfaction expressions in social media interactions?

The analysis of post-subscription user expressions provides indirect insights into factors that appear to drive subscription value perception. Users demonstrate high satisfaction with exclusive content access, enhanced user experiences and premium platform features through their positive sentiment expressions. The predominant positive sentiment and high engagement levels suggest that these benefits align with user expectations and needs, indicating they likely serve as motivational factors for subscription adoption.

However, these findings represent inferred motivational factors derived from post-subscription satisfaction expressions rather than direct measurement of pre-subscription decision-making processes. The UGT framework supports the interpretation that users value paid subscriptions for their ability to fulfill information, entertainment and social interaction needs more effectively; however, this conclusion is drawn from observed satisfaction patterns rather than stated motivational data.

Sentiment analysis

The sentiment analysis revealed a predominantly positive sentiment among users, with 79.97% of comments classified as positive. This high level of positive sentiment indicates significant user satisfaction with the platform's offerings, including paid subscriptions. The relatively low percentage of negative comments (9.95%) suggests that while there are areas for improvement, the overall user experience is favourable. The sentiment distribution analysis, particularly when correlated with engagement metrics such as likes and replies, underscores the importance of maintaining a positive user sentiment to enhance engagement and satisfaction.

Theoretical implications

The findings of this study align with several theoretical frameworks:

NET

The positive sentiment and high engagement levels reflect the benefits of network externalities, where the value of the platform increases as more users join and engage with the content. Paid subscriptions, by enhancing the content quality and user experience, likely contribute to this network effect, attracting more users and fostering a more vibrant community (Anderson *et al.*, 2023).

UGT

Users express significant positive engagement and appreciation, which can be explained by UGT. Users seek out content that fulfills their needs for information, entertainment and social interaction. The high frequency of keywords like 'thanks', 'love', 'amazing' and 'helpful', indicates that the platform effectively meets these needs, leading to higher user satisfaction and engagement.

CET

The themes identified through topic modelling, such as Positive Engagement and Appreciation, Constructive Feedback and Agreement, and User Helpfulness and Support, highlight the active participation of users in the platform (Suzianti *et al.*, 2019). CET emphasises the importance of emotional and behavioural engagement, which is evident in the users' frequent interactions, expressions of gratitude and constructive feedback (Chen *et al.*, 2017). This engagement is crucial for building a loyal user base and fostering a supportive community.

Practical implications

The practical implications of this study are significant for platform developers and content creators. The positive user sentiment and high engagement levels suggest that paid subscriptions can be an effective monetisation strategy if managed well (Jhang-Li & Liou, 2023). Continuous monitoring of user feedback and sentiment is essential to maintain and enhance user satisfaction (Kim & Kim, 2020). The constructive feedback provided by users should be valued and used to guide platform improvements and content development.

Additionally, the analysis highlights the importance of delivering high-quality content that users are eager to share, as reflected in the high frequency of keywords related to content quality and sharing (Park & Lee, 2021). Fostering a supportive community where users assist and uplift each other can further enhance the user experience and drive engagement.

In conclusion, this study underscores the significant impact of paid subscriptions on user engagement and revenue growth in social media platforms. By leveraging theories such as NET, UGT and CET, the research provides a nuanced understanding of user behaviours and sentiments. The predominantly positive sentiment and high engagement levels indicate that paid subscriptions, when implemented effectively, can enhance user satisfaction and contribute to the platform's success. Continuous monitoring, responsiveness to user feedback, and a focus on delivering high-quality content are essential strategies for maximising the benefits of paid subscriptions and fostering a vibrant, engaged community.

A significant limitation of this study is that sentiment analysis of post-subscription social media comments provides indirect rather than direct insights into user motivations for subscription adoption. While positive sentiment expressions and engagement patterns suggest factors that contribute to subscription value perception, these findings cannot definitively establish the causal relationships between specific features and initial purchase decisions. The methodology captures post-adoption satisfaction and engagement rather than pre-adoption motivational factors, requiring careful interpretation of motivational inferences drawn from the data. This study does not include actual revenue data or financial performance metrics. The findings demonstrate user engagement and satisfaction patterns that may indicate subscription model effectiveness but cannot directly establish revenue growth impacts. Future research incorporating actual financial data would be necessary to validate the revenue implications suggested by these user behaviour patterns.

Future research

This study provides valuable insights into the impact of paid subscriptions on user engagement and revenue growth on social media platforms, with a focus on Instagram. However, several areas warrant further investigation to build on these findings and explore additional dimensions of this topic.

Future research should employ direct methodological approaches to investigate subscription motivations, such as survey research examining pre-subscription decision-making factors or longitudinal studies tracking users from initial consideration through to adoption and ongoing engagement. Such studies would complement the current sentiment analysis findings by providing direct evidence of motivational factors rather than post-subscription inferences.

Future research could extend the analysis to include multiple social media platforms such as Facebook, TikTok and YouTube. Comparing user engagement and sentiment across different platforms can provide a broader understanding of how paid subscriptions influence user behaviour in diverse digital environments. This comparative approach could also reveal platform-specific factors that affect the success of subscription models. While this study covered a one-year period, extending the timeframe to multiple years could offer deeper insights into long-term trends and patterns in user engagement and sentiment. Longitudinal studies can help identify sustained impacts of paid subscriptions and how user preferences evolve over time. This extended analysis would also allow for the examination of the long-term effects of significant platform updates or changes in subscription models. Future research could incorporate more advanced sentiment analysis techniques, such as deep learning

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models and contextual embeddings, to enhance the accuracy and depth of sentiment classification. These advanced methods could better capture nuances in user comments, such as sarcasm, irony and complex emotional expressions, providing a more detailed understanding of user sentiment.

Investigating the influence of social media influencers and content creators on the adoption and perception of paid subscriptions can provide valuable insights. Future studies could analyse how endorsements or criticisms from popular influencers impact user sentiment and engagement with subscription features. This line of research could also explore strategies for leveraging influencer partnerships to boost subscription adoption. Analysing user engagement and sentiment based on demographic factors such as age, gender, location and socioeconomic status could reveal important differences in how various user segments perceive and interact with paid subscriptions. Segmenting the user base can help identify targeted strategies for different demographic groups, enhancing the overall effectiveness of subscription models. While this study focused on user engagement and sentiment, future research could examine the direct impact of paid subscriptions on revenue metrics and overall business performance. Investigating metrics such as subscriber retention rates, average revenue per user and lifetime value can provide a comprehensive understanding of the financial benefits of subscription models. This analysis could also explore the cost-benefit dynamics of implementing and maintaining subscription features. Examining the impact of paid subscriptions in different cultural contexts can provide insights into how cultural factors influence user engagement and sentiment.

Cross-cultural studies can identify cultural preferences and sensitivities that affect the acceptance and success of subscription models, helping platforms to tailor their strategies to diverse global audiences. Future research should also address ethical considerations related to user data collection and privacy in the context of paid subscriptions. Investigating user perceptions of data privacy and trust can help platforms develop transparent and ethical practices that build user confidence and loyalty. By exploring these areas, future research can deepen our understanding of the multifaceted impacts of paid subscriptions on social media platforms and provide actionable insights for enhancing user engagement, satisfaction and business performance.

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Modelling and Analysis of Regulatory Interventions for Sustainable Public Wi-Fi Programs

The Case of India

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Abstract: Public Wi-Fi is a suitable technology alternative to mobile broadband for affordable Internet access. With a 2.6 billion population globally yet to be connected, many countries are formulating policies around public Wi-Fi to bridge the digital divide. India lags considerably, where only 44% of rural residents have broadband Internet access. Public Wi-Fi penetration in India is meagre compared to global deployments. The Indian Government launched the Wi-Fi Access Network Interface (WANI) as an approved public Wi-Fi infrastructure project in December 2020, with the dual objectives of encouraging local entrepreneurs to become Public Data Offices (PDOs) and offering citizens affordable high-speed Wi-Fi Internet service. However, the scheme has so far met with limited success due to factors such as high backhaul charges and price-based competition from existing service providers. The sustainability of these PDOs is critical for the success of the program. We developed an agent-based model of the WANI ecosystem by incorporating the Bass diffusion model for users' adoption of Internet data service offered by PDOs. Our simulations indicate that offering a one-time subsidy, capping the market share of individual PDOs, and mandating a lower Internet backhaul tariff for this project will lead to more sustainable and competitive Wi-Fi markets.

Keywords: public Wi-Fi, digital divide, Internet broadband, agent-based model, Internet backhaul

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Introduction

Wi-Fi networks complement cellular mobile broadband services offered by licensed telecommunications and Internet service providers (TISPs) through providing superior indoor coverage. The TISPs also benefit by offloading part of the traffic from the cellular network, thereby potentially reducing network congestion. The Wi-Fi hotspots are made available primarily by the Internet service providers (ISPs) in public places such as hotels, shopping areas, airports and railway stations, using subscription or advertisement-based business models. The total number of public Wi-Fi hotspots worldwide has increased from 100 million in 2016 to more than 550 million (Statista, 2024). For example, in India, RailTel a subsidiary of Indian Railways, provides Wi-Fi broadband access in over 6,000 railway stations across the country.

The WiFi4EU initiative promoted by the European Union (EU) has the goal of providing free access to Wi-Fi connectivity for citizens in public spaces, including parks, public buildings, libraries, health centres and museums in municipalities throughout Europe (Navío-Marco *et al.*, 2019; Van den Velden & Sadowski, 2023). Countries like the Philippines have initiatives such as 'Free Wi-Fi for All' with similar policy objectives of bridging the digital divide (Serafica *et al.*, 2023). The development of public Wi-Fi networks in the various states of the United States was primarily envisioned as a low-cost alternative to commercial offerings but rarely fulfilled social inclusion and development objectives (Fraser, 2009). These programs did not succeed due to regulatory complications of market distortion and the discouragement of private investment, especially in about 200 municipalities including Philadelphia, San Francisco and Chicago where the public Wi-Fi movement initially started (Chesley, 2009; Wilson, 2021).

The acute need for public Wi-Fi became apparent during COVID-19. Some school districts in the United States provided temporary Wi-Fi hotspots to students within 150 to 200 feet of buses to support distance learning (Lai & Widmar, 2021). Sieck *et al.* (2021) highlight the importance of public Wi-Fi hot spots for accessing health information in rural and remote areas. Pahlavan & Krishnamurthy (2021) document a detailed holistic overview of the evolution of Wi-Fi technology and its applications in our daily lives.

However, public Wi-Fi coverage in India is inferior. Public Wi-Fi hotspots per million people in the United Kingdom, the United States and China are respectively 175, 50 and 75 times that of India (Parbat, 2023). Noting the lack of public Wi-Fi infrastructure in India, the Telecom Regulatory Authority of India (TRAI) initiated discussions on an open Wi-Fi access protocol in 2016–17 and conducted many stakeholder meetings. The TRAI recommended an open standard specification referred to as Wi-Fi Access Network Interface (WANI) in 2017 (TRAI, 2017). Subsequently, the government of India launched the Prime Minister WANI (PM-WANI) scheme, as approved by the Cabinet in December 2020, to improve affordable Wi-Fi access for the netizens of India (GoI, 2020).

By way of example, under the WiFi4EU initiative, municipalities received funding of up to approximately EUR 15,000 during 2018 to 2020 from the European Commission to defer the cost of Internet connectivity and equipment maintenance (European Commission, 2024). The WANI scheme, however, was designed to foster an entrepreneurial ecosystem to provide sustainable Internet access without any state subsidy, but the scheme was not successful. To date, there have been few successful business models for public Wi-Fi, and most remain experimental (Potts, 2014).

In this context, we analyse various factors that affect the deployment of such large-scale public Wi-Fi projects and characterise them using agent-based modelling (ABM). We simulate various scenarios and prescribe regulatory interventions for a sustainable public Wi-Fi initiative.

In the next section, we discuss the WANI project's specific technical architecture and economic characteristics. In Section 3, we develop an ABM and explain the model parameters. In Section 4, we present simulations of various scenarios and discuss findings. In the last section, we propose regulatory interventions based on our findings and indicate our research's limitations.

The Existing Framework of Public Wi-Fi Schemes

WANI is a technical and regulatory innovation that unbundles the Wi-Fi ecosystem to provide affordable and ubiquitous high-speed Internet access. Most Wi-Fi deployments, either enterprise or public, are provided by a single entity. In most cases, the ISP or TISP provides these functions. This may be due to existing telecommunications regulations where only licensed entities, such as ISPs and/or TISPs, can offer Wi-Fi services. Besides regulatory limitations, it is also driven by business cases where a single entity controls all network components, including backhaul and access. Such a controller is justified in cases where deployment is confined to an enterprise or small-scale deployment. However, large-scale deployments can only be achieved if the ecosystem is unbundled, where separate/independent functions are offered by different entities and integration/interoperability is taken care of by well-defined interface, application program interface (API), message flow and standards (Tatsumoto, 2021).

The WANI architecture is designed to be highly scalable and distributed across different telecommunications layers. It is interoperable at each layer and provides end users with a seamless and secure Wi-Fi experience. Another objective of WANI is to create an abundance

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of last-mile Wi-Fi access providers in the form of micro-entrepreneurs so that the proliferation of the Wi-Fi network is fast and easy (GoI, 2020). The WANI architecture, by design, enables the layered approach where a separate player supports each function of the Wi-Fi ecosystem. This renders the architecture scalable from a technical point of view and low cost from an economic point of view. The model envisioned setting up public Wi-Fi hotspots in Public Data Offices (PDOs) by local entrepreneurs with methods for monetising Internet services, at the same time providing affordable Internet access to users. The ISPs and TISPs viewed this as a threat to their existing broadband businesses and resorted to strategies such as fixing high backhaul charges to make this initiative unsustainable for the local entrepreneurs. The WANI ecosystem consists of the following:

1. **PDO**, which is established across the country by local entrepreneurs to maintain and operate WANI-compliant Wi-Fi access points (APs) and deliver broadband services to subscribers.
2. **Public Data Office aggregator** (PDOA), who with local knowledge, acts as an aggregator of PDOs and performs the functions relating to authorisation, accounting and security as built in the WANI architecture.
3. **App providers**, who develop applications to register users and discover WANI-compliant Wi-Fi hotspots in the nearby area and display the same within the app for accessing the Internet service.
4. **Central Registry**, that maintains, by the WANI architecture and specifications, the details of app providers, PDOAs and PDOs and enables interoperability among these independent entities of an ecosystem based on open WANI standard.

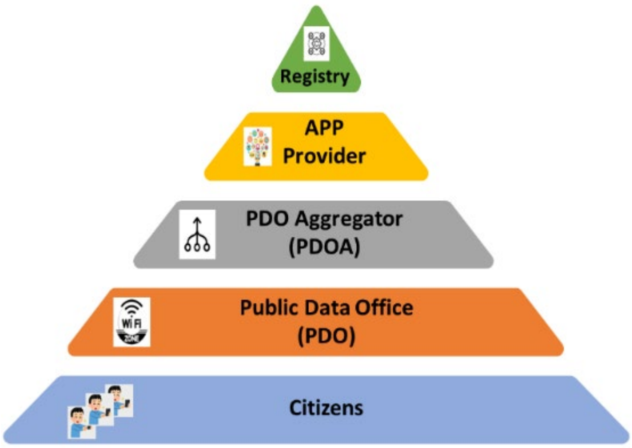

Figure 1. The schematics of the WANI ecosystem. (Source: authors' own)

Figure 1 schematically illustrates how the players listed above stack up in the WANI ecosystem. The WANI network consists of a Wi-Fi access point maintained by the PDO that is connected to the Internet backhaul provided by an ISP. A user sees the service set identifier (SSID) on the WANI application installed on the user's device, which is broadcast by the access point, clicks it and gets connected to access the Internet.

The total number of WANI hotspots in India is around 250,000 and increasing (Figure 2). However, this falls very much short of the envisioned target of 10 million hotspots in the Indian National Digital Communications Policy 2018 (GoI, 2018). As of October 2024, the number of PDOAs is around 201, out of which the state-owned TISP (namely, Bharath Sanchar Nigam Limited) accounts for about 20% of the commissioned WANI hotspots. Close to 50% of the PDOs are with a single private firm, indicating PDO market concentration.

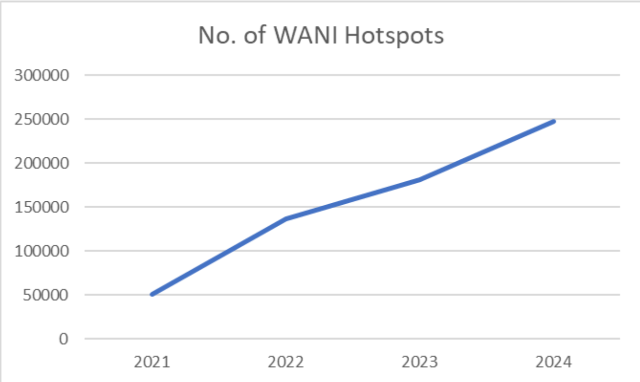

Figure 2. Growth of WANI hotspots over the years. (Source: authors' own)

Reasons for market failure

The PDOs, usually owned and operated by local entrepreneurs, install the Wi-Fi network using Wi-Fi APs to provide Wi-Fi connectivity within their premises (indoor) or limited outdoor surrounding areas. They procure Internet backhaul from the ISPs. There are two types of Internet backhaul services available from the ISPs: (a) Fibre to the home (FTTH) and (b) Internet leased line (ILL). The FTTH provides a shared connection to the ISP's Internet point of presence (PoP), while the ILL provides a direct logical/physical link to the PoP. Hence, ILL typically provides reliable downlink and uplink speeds compared to FTTH. The link speeds of FTTH and ILL in India typically range from 100 to 500 Mbps, respectively. The FTTH is designated as a retail service; hence, there are regulatory restrictions on the resale of bandwidth, whereas the ILL is a wholesale service. The TISPs provide affordable retail Wi-Fi access through FTTH, which competes with the WANI service.

The Internet broadband market in India is dominated by licensed TISPs, who also control the resale of backhaul bandwidth required by the PDOs for their WANI networks. The significant costs of setting up the WANI are due to the Internet backhaul charges. The WANI policy mandates that the PDOs enter into a commercial agreement with the TISPs regarding backhaul (GoI, 2020). The TISPs offer the ILL services at a commercial tariff, 30 to 40 times more than their retail FTTH tariff, as shown in Table 2. Hence, the PDOs are forced to pay very high charges for their ILL backhaul connections on the supply side while at the same time facing the competitive home broadband service offered by the same TISPs on the demand side.

Further, India is a 'mobile first' market, with more than one billion users accessing mobile broadband services (Venkatesh & Sridhar, 2014). In addition, TISPs have been aggressively pricing their data plans, with India ranked seventh worldwide in terms of the lowest tariff for mobile broadband at an average of USD 0.16 per gigabyte (GB) (Cable.co.uk, 2025). This poses substantial demand uncertainty for public Wi-Fi operators, especially in urban areas.

Therefore, it has become difficult for PDOs to scale up due to high fixed and recurring costs and competition from the TISPs. The moot question is whether a scheme like WANI requires regulatory interventions such as state subsidies, tariff capping, capping on market share etc. to provide momentum for the growth of public Wi-Fi schemes across the country. Fraser (2009) well documents the failure of public Wi-Fi in US cities, mainly due to the high set-up costs of Wi-Fi networks by the municipalities and the availability of economical home broadband and mobile broadband from the TISPs. In the case of WANI, regulatory interventions shall enable not only economical broadband Internet to a price-sensitive population, but also the promotion of local entrepreneurship in the form of PDOs.

Regulatory Options for the Sustainable Public Wi-Fi Scheme

Although the public Wi-Fi scheme's intention is to nurture local entrepreneurship in setting up PDOs to provide sustainable low-price service as an effective alternative to a mobile broadband service, opposing forces such as restricted competition and high costs have hindered its penetration. The next section reviews three regulatory interventions that can alter the scenario.

Price cap regulation

Since price cap regulation (PCR) was introduced in the United Kingdom in 1984, price caps that set the ceiling price for retail services have been used by telecommunications regulators around the world to check price increases. It has been observed that PCR has been effective in containing prices in non-competitive markets (Xavier, 1995). However, some studies indicate that PCR has an adverse effect on quality of services (Façanha & Resende, 2004). Although PCR in the wholesale telecommunications market is scarce, recent studies in wholesale electricity markets indicate that temporary price caps tend to prevent higher price mark-ups by firms and improve market outcomes (Sirin & Erten, 2022). A recent study highlights the effect of PCR for wholesale roaming arrangements in the EU and the effect of lobbying by various stakeholders on the level of price caps (Alves *et al.*, 2021).

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With regards to the WANI model, since the backhaul is provided by the incumbent TISPs to the PDOs, and there is limited competition in the wholesale backhaul market, there is a case of PCR to be applicable to the wholesale backhaul tariff. As indicated in the aforementioned literature, it might have the effect of reducing prices and orderly market outcome, at least in the short run. The cost-based regulation, under which the regulator defines the access price equal to the marginal cost of providing access plus a fraction of the cost of the investment undertaken by the incumbent firm as the basis for fixing tariff cap, though widely used has some limitations (Sarmento & Brandao, 2007). In this model, unless there is verifiable cost information, the tariff cap fixed by the regulator may be arbitrary and in some cases may be more than the cost structure of the service providers, thereby defeating the very purpose of such cost-based regulatory intervention. Hence, it is very important to estimate the tariff cap based on reliable audited cost estimates.

Subsidy models

When the market fails, especially when the private entities incur higher cost of services, state subsidy is typically considered to support a program (Kalish & Lilien, 1983). These subsidies become necessary to correct market failures such as demand uncertainty, high initial investment costs and information asymmetry (Potts, 2014). In most countries, including India, the licensed telecommunications operators pay a universal service levy (USL) as a percentage of revenue towards a Universal Service Obligation fund (USOF). The state compensates the operators through this fund for their high-cost rural and remote area connectivity (details of USOFs in India are provided in Sridhar (2012)). The USL reflects the belief that telecommunications licensees needed to give back to society for the privilege of being chosen to provide telecommunications services without being burdened with a universal service obligation in unviable areas. Based on the historical data of 223 high-tech enterprises in Japan, Koga (2005) proved that subsidies favourably impact enterprises' development.

However, there are several regulatory decisions to be made with subsidies: (i) how much to subsidise, (ii) how long to subsidise, and (iii) who to subsidise – consumers or service providers. Grants and subsidies lower the effective price for consumers, thereby stimulating demand. The economies of scale achieved reduce the average cost of the service, thereby making it sustainable. It also reduces the capital burden on suppliers and helps them to sustain their businesses due to demand uncertainty (Kalish & Lilien, 1983; Potts, 2014). Hence, the objective is to determine the optimal subsidy policy to attain the stated objective in an efficient manner.

The demand side of direct subsidy for broadband service enabled by the Affordable Connectivity Program (ACP) in the United States has been extensively studied by Horrigan *et* *al.* (2024). They point out that households' social and economic connectedness plays an important role in beneficiary enrolment. The effects of both supply-side and demand-side subsidies in the context of digital terrestrial television (DTT) in Indonesia are provided by Ariansyah (2022). They studied how subsidising the DTT decoders to households while increasing competition amongst the DTT device manufacturers has positively impacted this adoption. There have been many studies on demand-side subsidies of handset bundling. A detailed analysis of handset bundling with mobile telecommunications services and their effect on social welfare in the Korean market is illustrated in Lee & Park (2016). The effect of government subsidies on the telecommunications industry, modelled using a three-player oligarch game, in the Chinese market is studied by Ma *et al.* (2022).

In general, users expect Wi-Fi offerings in public places to be charged at lower prices, and more often for free, as it complements mobile broadband. However, as indicated earlier, the wholesale backhaul bandwidth prices, as fixed by the TISPs, are high enough for public Wi-Fi operators to provide their services at affordable, lower prices. Studies were conducted on the regulator's trade-off of reducing the wholesale price for third-party providers (TPP). While this decreases retail price, promotes the entry of more TPPs and increases consumer welfare, it is likely to decrease the revenue of the incumbent TISPs and hence the incentive for TISPs to invest in networks (Ross, 2024). Further, a counterargument states that any investment in networks is considered as a sunk cost and therefore does not depend on the revenue earned by the TISPs (Alleman & Rappoport, 2006).

In reality, the Internet data market is highly competitive due to existing ISPs and TISPs and follow competition-based pricing rather than cost-based pricing, which is derived by taking into consideration the price levels defined by existing competition in the market (Mikail, 2019). Hence, PDOs are forced to charge a competitive price to the user for data volumes while incurring heavy costs to build and run the PDO business. This has been cited as one of the reasons for the failure of WANI. Per GB data pricing per day in the range of INR 1–3 is derived by comparing prevalent pricing of 4G cellular data (~INR 10 per GB) as per latest TRAI performance data (TRAI, 2024a), and FTTH home broadband and discounting to get competitive advantage.

Outlined below are selected subsidy models and the associated challenges:

1) Subsidy to cover the loss of PDOs: Since the program's objective is to create a financially sustainable business model for local entrepreneurs, a subsidy to offset the losses incurred during the initial stages of operations may be an option. However, the subsidy may deter the PDOs, either by growing subscriber revenue or reducing the

costs of their services. Estimating the expected losses and encouraging the PDOs to become profitable in the future are this model's challenges.

2) Subsidy as a percentage of revenue earned: The subsidy is provided as a percentage of earned revenue and given to all PDOs, as there is no exclusion criterion. However, in this case, the efficient and profitable PDOs can scale up quickly with the given subsidy, resulting in possible monopolisation of the market.

3) One-time subsidy to cover the fixed cost: In this method, a portion of the fixed cost of deploying the access points, cabling, antenna, enclosure and fixtures is provided to all PDOs to reduce the average cost of operation. This method gives the PDOs almost the same subsidy amount. The efficient PDOs will be able to sustain themselves during the initial stages. Leveraging on the network effect, the few PDOs who sustain themselves during the initial period will be able to subsequently gain market share. The market is expected to be an oligopoly, with a few PDOs dominating the market.

Researchers have analysed the above models in the context of telecommunications and technology industries. In their recent paper, Ma *et al.* (2022) indicate that a one-time lump sum subsidy has the needed effect on regulatory impact. Hence, in this paper, we analyse the effect of a one-time lump sum subsidy as it is administratively easier and promotes a relatively more efficient PDO market.

Capping the number of users

In the WANI scheme, the objective is to introduce as many PDOs as possible to encourage local entrepreneurship while providing Internet access to a large user base. At the same time, price capping as a regulatory intervention has been studied in detail (Rey & Tirole, 2019). There have been many studies on data capping for broadband use and its effect on competition and consumer welfare (Dai *et al.*, 2014). It must be noted that capping on broadband data or speed by the service providers is to enable better management of traffic prioritisation and congestion. Although uncommon, any cap on the number of users is likely to promote competition in service provisioning.

The mapping of users to each service provider enables equitable distribution of the users to available PDOs, thereby improving competition in the market. However, a lower cap may reduce the number of users of each PDO to a level at which the PDO will not be able to recover costs and make a profit. At the same time, a higher cap may result in non-optimal use of PDO resources, such as Wi-Fi hotspots and the leased backhaul capacity. Hence, it is important to design an optimal capping so that the stated objectives can be realised and the market is stable with sufficient competition.

For example, one Wi-Fi Access point connected to an Internet backhaul with 100 Mbps speed and 3,000 GB of data volume in a month can serve up to 50 users with up to 2 GB of data per day to utilise its network capacity to the maximum. If the PDO serves a smaller number of users than its maximum utilisation, the revenue earned will not be sufficient to recover the fixed cost. Further, the fixed cost is a step function of the number of users. For example, in the case mentioned, if the number of users is more than 50 then the capacity upgrade is available only in discrete quantities, requiring additional fixed cost.

Agent-Based Modelling of the WANI Scheme

We use ABM to understand the impact of the regulatory interventions on the financial sustainability of the WANI scheme. ABM enables the simulation of heterogeneous agents such as PDOs and Wi-Fi users. The interaction between the agents and the system's resultant behaviour form the patterns operating in the real world (Hamill & Gilbert, 2015). As a deductive approach, ABM enables modellers to define rational agents' behaviour using well-defined mathematical equations. On the other hand, the abductive approach in ABM enables the emergent behaviour of systems with multiple agents and their interactions over many iterations (Schinckus, 2019).

Modelling such an extensive socio-technical system with many stakeholders ought to provide insights into how micro-level changes impact emerging system behaviour (Vila *et al.*, 2004). Drawing on the extant literature on using ABM to derive macro policy decisions from micro behavioural characteristics, we build a model to simulate the working of the WANI scheme. Although the non-linearity of complex systems can be modelled using conventional analytical methods, it can be insufficient as interactions between variables are not captured in full (Schneider & Somers, 2006; Sterman, 2000). The simulation results from ABM can provide guidelines to regulators and policymakers for effective intervention.

The WANI ecosystem consists mainly of two agents/actors in the system: (i) users who consume the service and (ii) PDOs which provides the last mile of Wi-Fi connectivity and associated services to users. In the following subsections, the calibration and parameterisation of the ABM are provided.

Diffusion of innovation model

We use a diffusion of innovation theory pioneered by Rogers (2003) to model the growth of Wi-Fi users. The Bass diffusion model is a widely used mathematical model for technology diffusion and has been widely used by research to model Internet adoption and mobile services adoption (Bass, 1969; Jha & Saha, 2025) and is given by:

$$n(t) = \frac{dN(t))}{dt} = \left(p + q\,\frac{N(t)}{M}\right)(M - N(t)) \tag{1}$$

The various parameters of the model in Equation 1 are provided in Table 1.

Table 1. Parameters of the Bass diffusion model

N(t)	Cumulative number of adopters at time *t*
n(t)	The number of adopters at the time *t*
M	Maximum number of potential adopters
$p \in \{0.1\}$	Innovation co-efficient
$q \in \{0.1\}$	Imitation co-efficient

(Source: authors' own)

The growth of the Wi-Fi user base depends on innovation and imitation factors. Innovators adopt an innovation independently without any other external influence, while imitators adopt an innovation based on others' feedback and experiences (Rogers, 2003). In our model, the values of p and q are set at two different levels to simulate a faster or slower diffusion process. Some researchers have empirically derived p and q from time series data (Jha & Saha, 2025). However, due to the unavailability of data on Wi-Fi users in India, we normalise the values of p and q with higher and lower p and q values, resulting in faster or slower adoption, respectively.

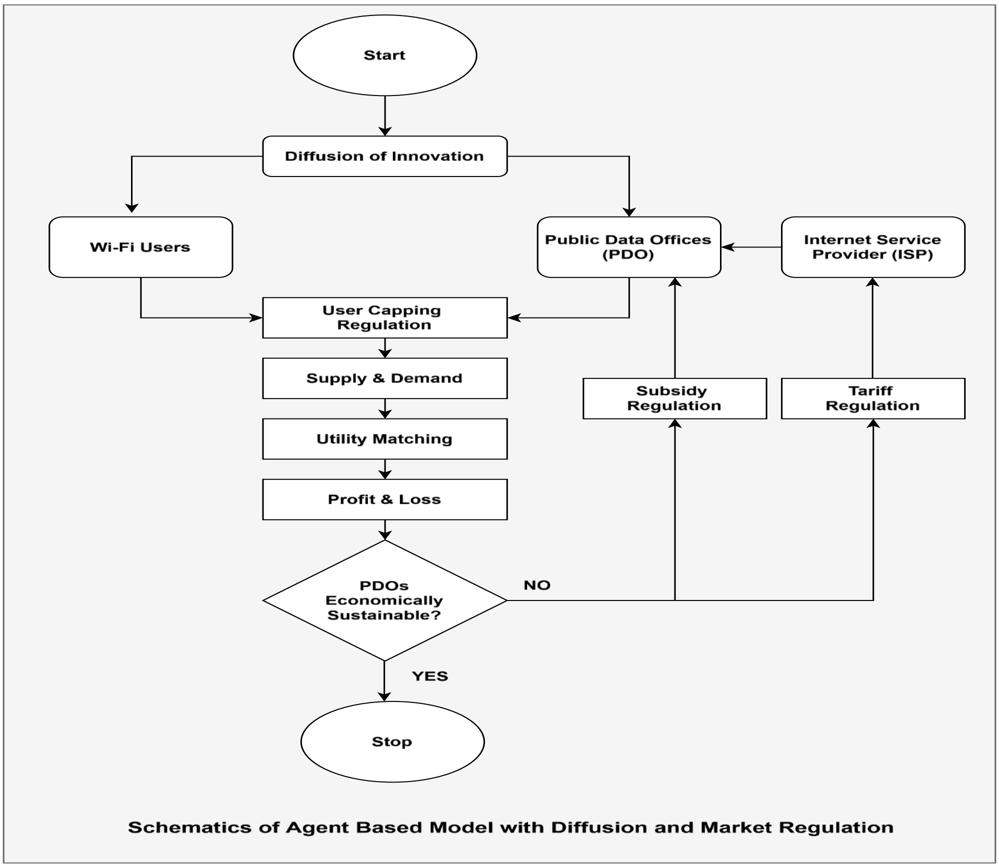


Figure 3. Schematics of the agent-based model simulations. (Source: authors' own)

We simulate high and low rates of diffusion of user base to understand the market equilibria in two extreme cases and derive the bounds. Figure 3 provides the schematics of our model.

Calibration of Internet backhaul models

The PDOS can provide the WANI services indoors within the premises (that is, Internet centre/cybercafé) or both indoors and outdoors with extended coverage. While one to two APs are required for indoor connectivity, more will be required to provide outdoor connectivity. However, outdoor connectivity is expected to draw more demand as users can be nearby and still access the Internet. Since the number of users and devices is expected to be more than indoor, the bandwidth required for Internet backhaul is also higher. We model various types of WANI deployment, and the corresponding cost estimates based on the price of APs and backhaul tariffs charged by the various ISPs are provided in Table 2.

Table 2. Wi-Fi access network cost structure

PDO configuration	Access network cost in INR	Backhaul cost in INR (yearly)	Total fixed cost (for one year) in INR
Indoor FTTH	5,000	20,000	25,000
Outdoor FTTH	10,000	40,000	50,000
Indoor ILL	5,000	4,00,000	405,000
Outdoor ILL	10,000	1,100,000	1,110,000

Note: These costs are derived by comparing data plans from leading ISPs in India. (Source: authors' own)

Supply demand matching process

The model's parameters are provided in Table 3. The users are generated using the diffusion model in Equation 1. Each user has a utility function, U_i, which is a function of price and quality. Since the PDOs are local entrepreneurs, the users are also aware of a PDO's reputation, which also affects their utility. The users select to attach themselves with the PDO, which provides maximum utility. Under the capping model, as the user base for a PDO reaches the ceiling N set by the regulator, then users are forced to shift to the next preferred PDO and so on. Under the subsidy model, each PDO receives a fixed subsidy S for a defined period to defray the cost of APs and backhaul connectivity. At the end of each planning period, the PDOs calculate their profit/loss. The profit-making PDOs remain in the market while the loss makers exit. The PDO who remains in the market, improves its network quality and reputation. It also reduces the price to attract more users, as long as profit threshold is met.

As indicated in Table 3, we assume a uniform distribution for users' affinity towards price, quality and reputation (Valera & Gomez-Rodrigue, 2015). The primary reason for choosing one uniform distribution over the others is that the set of users in a locality served by the PDOs is relatively homogenous. In order to simulate the heterogeneity of PDOs, the price, quality and reputation of services offered by the PDOs are drawn from a normal distribution. This provides a marketplace wherein each PDO offers differing {price, quality, reputation} to distinguish itself. The flow diagram of the simulation process is provided in Appendix 1.

Table 3. Simulation parameters of the model

I	Set of all users; $\|I\| = M = 500$
J	Set of all PDOs; $\|J\| = 10$
α_i	User i's affinity towards price; $\alpha_i \in U(0,1)$
β_i	User i's affinity towards quality; $\beta_i \in U(0,1)$
di	User i's data consumption per day; $d_i \in U(0.5,2)$
γ_i	User i's affinity towards the reputation of the PDO; $\gamma_i \in U(0,1)$
p_j	Price charged by the PDO j for the Wi-Fi service; $p_i \sim N(2,0.1)$ and is non-negative for revenue calculation
q_j	Quality of service offered by the PDO j; $q_i \sim N(2,0.1)$
r_j	Reputation of the PDO as perceived by the users j; $r_i \sim N(2,0.1)$
U_i	Utility derived by the User I from a PDO j; $U_i = \beta_i q_j + \gamma_i r_j - \alpha_i p_j$
N_j	Number of users matched to PDO j
TC_j	Total cost incurred by PDO j while serving N_j users = fixed cost (FC) + variable cost (VC) - S
FC	The cost of a Wi-Fi access point, antenna, last-mile cabling from the ISP PoP to the service point, and Internet backhaul cost of FTTH or ILL is shown in Table 2 for FC for different deployment scenarios
VC	INR 0.10 per day per user to PDOA for aggregation platform charges
TR_j	Total revenue of PDO_j while serving N_j users $=\sum_1^{N_j} p_j d_i$
π_j	Profit earned by PDO j while serving N_j users = $TR_j - TC_j$
Th	Profit threshold (INR 1,000)
n_j	Number of users matched to PDO j at each step
$\bar{N}$	Regulatory capping on the number of users to be matched to each PDO. Optimum capping = 50, no capping = 500
S	Regulatory subsidy to the PDO. Derived by calculating average loss of loss-making PDOs after one-year period (INR 10,000)
T	Policy period. Simulation step definition (for one year, step = 360; for two years, step = 720; for three years, step = 1,080)

Source: authors' own

Model Results and Discussions

We developed various scenarios of interest in the deployment of the WANI model as indicated below, by maintaining the wholesale backhaul price to PDOs equivalent to that of the retail FTTH pricing as indicated earlier.

We simulated the models shown in Figure 4 over a planning period of three years. Following are the significant interventions in the model:

1. The diffusion of adopters of the WANI scheme is as per Equation 1. The subscribers are assigned to the PDOs based on the utility value U_i calculated for each subscriber i across the set of all PDOs J as given by the equation for the same as given in Table 3.

2. In the case of scenario wherein no subsidy is provided by the government, loss-making PDOs exit the market.
3. In models where one-time subsidy is given, the subsidy amount is calculated based on the first-year cumulative loss incurred by the PDOs as in the case of the model without subsidy. This one-time subsidy is set to take care of the losses incurred by most of the PDOs in their first year of operation. If still some PDOs are at loss at the end of their first year, they exit. From the second year onwards, if any of the PDOs still make losses, they exit as shown in the flow diagram in Appendix 1.

Summary of the simulation results over a three-year planning period are shown in Table 4 and Figure 5a and Figure 5b.

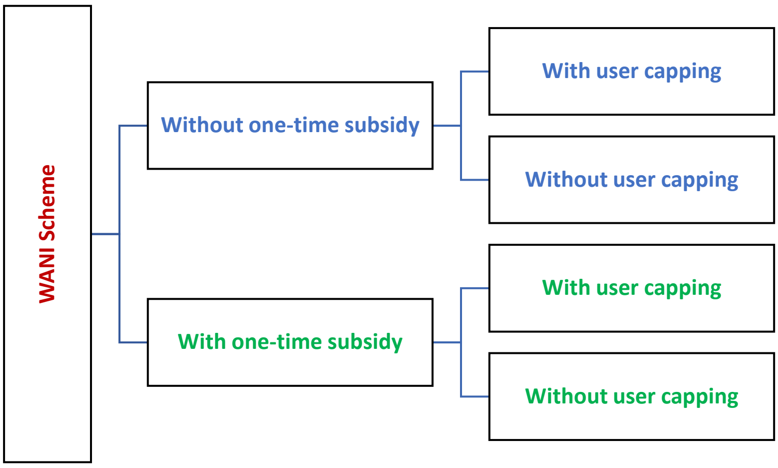


Figure 4. Simulation scenarios (Source: authors' own)

Table 4. Summary of simulation results for slow diffusion

	No. profitable PDOs			
	No. subsidy + no. user capping	No. subsidy + user capping	Subsidy + No. user capping	Subsidy + user capping
Year 1	2	7	2	8
Year 2	1	4	2	7
Year 3	1	1	2	5
	Average cumulative profit per PDO per month			
	No. subsidy + no user capping	No. subsidy + user capping	Subsidy + no. user capping	Subsidy + user capping
Year 1	1,429	836	1,697	1,453
Year 2	8,220	1,484	6,402	544
Year 3	5,99	2,499	767	264
Avg. over 3 years	3,416	1,606	2,955	754

(Source: authors' own)

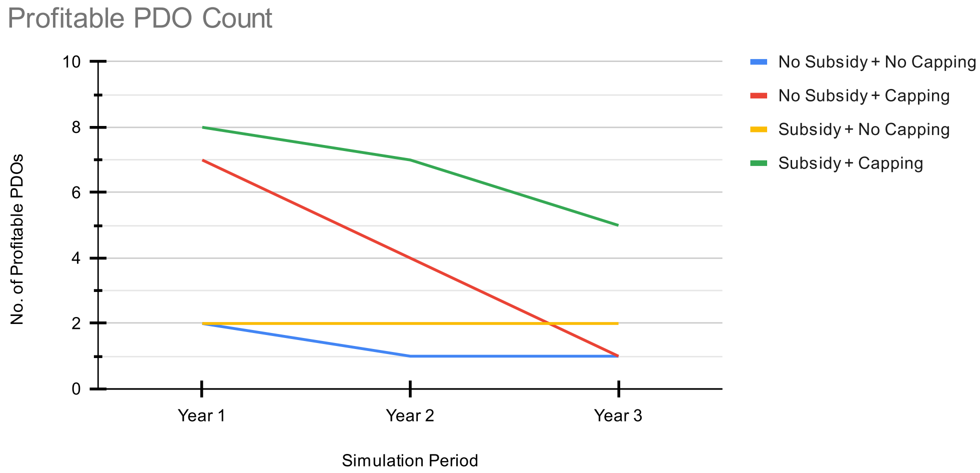


Figure 5a. Number of profitable PDOs year-wise. (Source: authors' own)

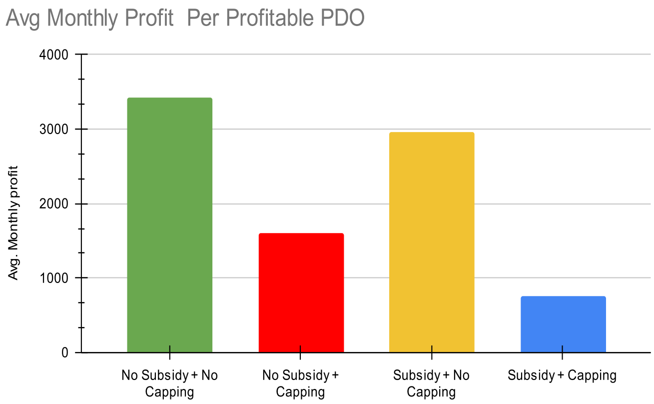


Figure 5b. Average monthly profit per profitable PDO over three years. (Source: authors' own)

Following are observations based on the simulation results:

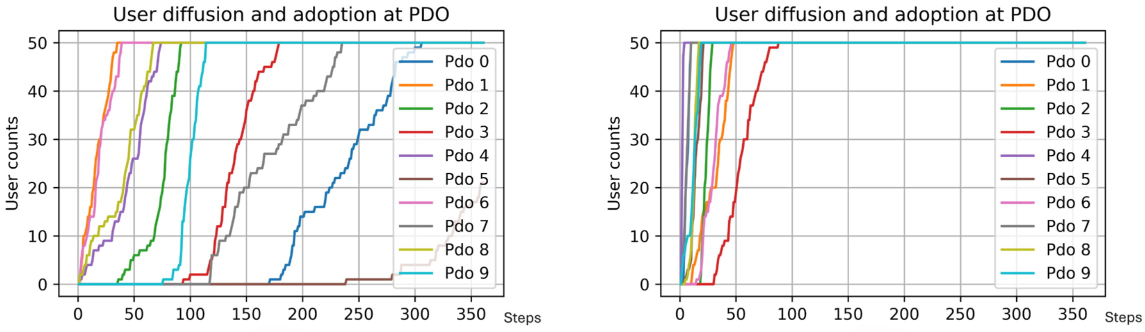
1. Without any one-time subsidy, the market tends to have a monopoly in the long run as most of the PDOs cannot sustain themselves due to the higher costs when increasingly more subscribers are onboarded. Due to the network effect and the economies of scale, it becomes feasible for one PDO to be profitable in the long run. With subscriber capping, although there are enough PDOs in the second year, it becomes a monopoly market from the third year onwards.

2. With subsidy, we witness a duopoly market without subscriber capping per PDO. This is due to the network and economies of scale effects.

3. However, the model with subsidy and subscriber capping results in a very competitive market with up to five PDOs existing with profitable businesses in the third year of operation. However, it is to be noted that under this scenario, the average profit reduces and is equitably distributed amongst the PDOs compared to the monopoly cases where the average profit is relatively much higher.

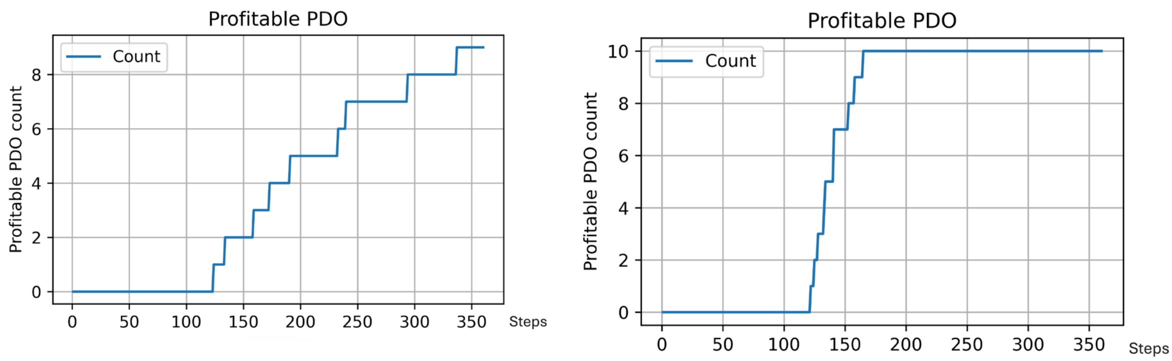
4. We also simulated a scenario with ILL backhaul at the existing prices and found that none of the PDOs are profitable, even in the long run. It must be noted that in most areas, especially in the rural parts of the country, ILL is provided by a monopoly TISP and hence the need for regulatory intervention on backhaul charges in such non-competitive markets.

We also simulated scenarios with slower and faster diffusion rates by changing the adoption and imitation coefficients in the Bass diffusion model. In general, with faster diffusion, Wi-Fi adoption reaches the maximum limits quickly, as shown in Figure 6 and Figure 7. This also results in a greater number of profitable PDOs compared to the case when the diffusion is slower. We find that the average profit per PDO with faster rates of diffusion is 30% to 40% more than that with a slower diffusion as shown in Figure 8. Research on diffusion models indicate that word of mouth and advertising will enable faster adoption.



(a) (b)

Figure 6. Adopter distribution across PDOs with (a) slow diffusion and (b) faster diffusion. (Source: authors' own)



(a) (b)

Figure 7. Profitable PDO count with (a) slow diffusion and (b) faster diffusion. (Source: authors' own)

Figure 8. Average monthly profit comparison for slow and fast diffusion. (Source: authors' own)

Conclusion

Our study indicates that public Wi-Fi projects such as WANI require an economic and regulatory analysis to create an ecosystem that is conducive for stakeholders to make it sustainable. A healthy, competitive market with a relatively larger number of profitable PDOs providing affordable Wi-Fi services is essential for the sustainability of such projects.

Tariff capping and its implications

Realising the need to reduce Internet backhaul costs, the telecommunications regulator in India (TRAI) has recently circulated a draft amendment of the ILL tariff for consultation. As per this draft proposal, the ceiling on the ILL tariff for PDOs, specifically for the WANI scheme, is proposed to be reduced to twice that of the home broadband FTTH connections (TRAI, 2024b; TRAI, 2025). This is expected to reduce the capex burden on the PDOs and, in turn, reduce the prices of Wi-Fi services offered by the PDOs. However, this tariff-capping proposal has been met with opposition from the TISPs. The TISPs argue that the drastic reduction in the wholesale ILL tariff will make their businesses unviable. Further, the reduction will also prompt many of their existing home broadband users to shift to the WANI scheme due to lower price options. However, it must be noted that while users with low data usage are likely to shift to the WANI networks, users who are data intensive and quality conscious are likely to retain their home broadband connections.

We also note that even with the FTTH pricing scheme, without subsidy we witness only two to three PDOs that become profitable in the short run and lean toward monopoly in long run. Such a scenario is acceptable in urban areas where the demand for Wi-Fi is relatively known and predictable. However, in semi-urban and rural areas, where the price elasticity of the users' demand is relatively high and there is demand uncertainty, a one-time subsidy is definitely required apart from a reduction in backhaul charges to make this project sustainable.

Regulatory recommendations

As indicated in our simulation study, the market will likely witness very few PDOs without capping the number of users per PDO. With optimal capping on the number of users to limit the market share in the short run, the market will likely tend towards more competition with a relatively larger number of PDOs. Similar situations have been witnessed in the digital payment sector in India, and limits on market share are being reviewed to prevent a duopoly market structure (*The Economic Times*, 2024).

Our simulation study indicates that some form of subsidy is needed to overcome the initial uncertainty and offset the fixed costs of setting up the PDOs. The entrepreneurial model without subsidies has not increased Wi-Fi penetration in the country. The USOF (also referred to as Digital Bharat Nidhi) is primarily intended to serve these types of requirements (Digital Bharat Nidhi, 2024). The existing USOF scheme that subsidises the telecommunications infrastructure in rural and remote areas of the country should be used for a one-time subsidy for all PDOs. As per our simulation, the acceleration of technology adoption also has a measurable impact on the sustainability of the PDOs. This can be done through mass awareness programs of the WANI scheme through traditional broadcasting and digital media by the government. Once the diffusion picks up and the user base starts increasing as per the Bass diffusion model, the economies of scale will enable the PDOs to generate revenue thereby making them sustainable. Infrastructure such as WANI has the potential to become a digital public infrastructure over which Internet services can be provided at minimal costs, both by businesses and governments, especially to netizens in the rural and remote areas of the country. With the above regulatory interventions, WANI can be self-sustainable, with many entrepreneurs venturing to become PDOs.

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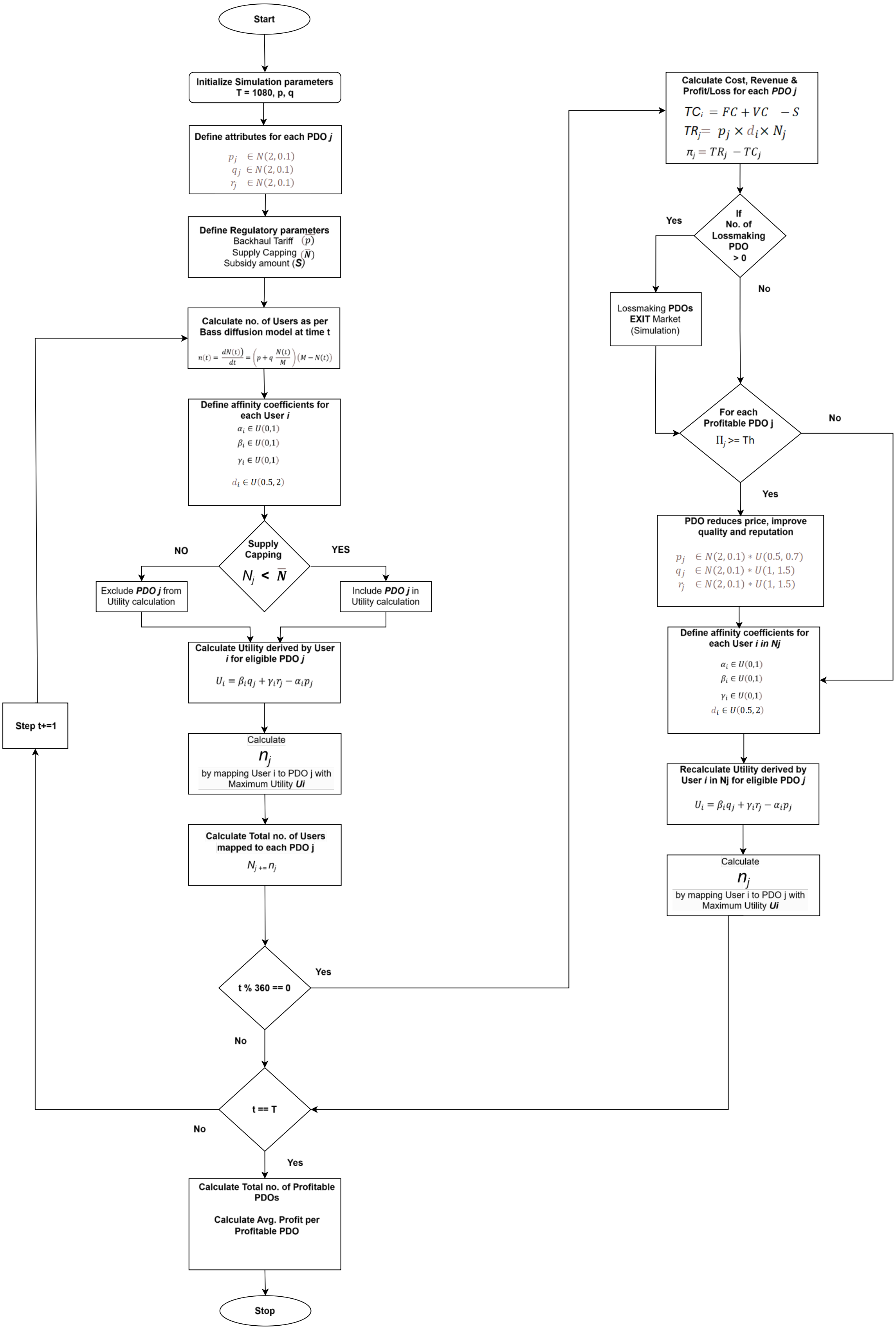
Appendix

A1. Flow diagram of the simulation process. (Source: authors' own)



Hybrid Deep Learning Ensemble with Dynamic Fusion for Reliable Anomaly Detection in Operational LTE RANs

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Abstract: Monitoring long-term evolution (LTE) network performance is increasingly complex due to rapidly growing data volumes and the diversity of quality-of-service indicators. Traditional monitoring approaches relying on static thresholds and manual key performance indicator (KPI) analysis often fail to detect multidimensional, evolving anomalies. We propose instead a hybrid deep ensemble learning framework for anomaly detection and diagnosis in Radio Access Networks (RANs). This framework integrates four complementary architectures: (i) a convolutional autoencoder (CAE); (ii) a Bidirectional Long Short-Term Memory AutoEncoder (BLSTM-AE); (iii) a transformer autoencoder (transformer AE); and (iv) a bidirectional LSTM forecaster, generating various anomaly scores. These scores are dynamically fused across frequency bands and processed with an Isolation Forest (IF) to produce the final anomaly judgment. An evaluation on real LTE data from Algerian mobile networks (three months, 1650 base stations, hourly KPIs) demonstrates the effectiveness of the proposed approach, achieving a maximum F1 score of 93.89%, an improvement of up to 9.5% over the best individual model. SHapley Additive exPlanations (SHAP)-based explainability analysis reveals that key operational indicators related to mobility and resource use drive the

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model's decisions. This work provides a practical, interpretable hybrid framework validated on confidential operational data from a national operator under region-specific conditions.

Keywords: Hybrid deep learning ensemble, LTE RAN KPI anomaly detection, Convolutional Autoencoder, Isolation Forest classification, SHAP interpretability.

Introduction

Mobile technology has significantly evolved in recent years. The advent of smartphones has particularly changed usage (Scatà, 2025). The deployment of LTE networks illustrates this change. It offers speeds significantly higher than previous generations and reduced latencies (Oshin *et al.*, 2016; Abrahams *et al.*, 2023). However, this development tends to complicate supervision, particularly due to denser sites, heterogeneous equipment, and mobile users. Ensuring quality of service generally involves continuous or periodic fine monitoring. According to Imoise *et al.* (2020), several indicators must be monitored: accessibility, data retention, mobility, and integrity.

In reality, analysis of Key Performance Indicators (KPIs) still relies heavily on manual inspections, often using traditional office tools. In fact, engineers examine the curves visually to spot anomalies. This method is cumbersome and error-prone (Zhao *et al.*, 2019; Sun *et al.*, 2023; Ma *et al.*, 2019). So, a file of several hundred thousand lines can easily saturate a spreadsheet, making analysis tedious. This poses several problems: anomalies are often detected late, the workload explodes, and small degradations sometimes go unnoticed. These difficulties are particularly evident in national networks, where an operator sometimes has to monitor several million subscribers.

Although anomaly detection in LTE networks has made significant progress, some grey areas remain. This is evident, for example, in practical cases such as handover failures or unpredictable congestion: current systems do not always identify them correctly.

The commercial solutions offered by major equipment manufacturers are not very transparent. According to Ericsson (n.d.), operators often have limited access to internal metrics in practice. In this case, incident analysis is performed with limited visibility, increasing the risk of misinterpretation.

The literature includes approaches based on complex architectures, such as Transformers or Graph Neural Networks (GNNs) (Ahmed *et al.*, 2025). The problem is that these studies are often validated on small, sometimes even artificial, datasets, which limits the scope of the conclusions (Gao *et al.*, 2025). Furthermore, the results obtained remain difficult for an operations engineer to interpret (Stoklasa *et al.*, 2024). According to Saidi *et al.* (2023), studies generally favour a single model, often at the expense of operator readability.

Indeed, regional specificities further complicate the analysis. In Algeria, for example, the coexistence of multi-generation infrastructures and the variability of rural/urban areas create rarely studied conditions. These findings suggest that more realistic approaches are needed: capable of providing reliable results on operational data, while remaining readable for engineers and adaptable to large-scale deployments.

In this work, we specifically address these challenges within the context of Algerian LTE networks. We leverage proprietary operational data to develop a region-specific anomaly detection solution. This paper proposes a hybrid deep learning ensemble for anomaly detection in Algerian LTE Radio Access Networks (RANs). It is a combined approach of spatial and temporal models to identify different patterns in multivariate KPI time series. Model-specific anomaly scores are aggregated using an adaptive, band-aware weighting strategy, ensuring that the most informative model prevails across varying network conditions. The aggregated score is then passed through an IF-type meta-classifier. An explainability module based on SHAP was used to enhance operator confidence and support diagnosis. It highlights the features that most influence detection. The main contributions of this work can be summarized as follows:

1. Hybrid deep learning: We used a hybrid approach combining several autoencoders (CAE, BiLSTM-AE, Transformer-AE) with a BiLSTM forecaster. The idea is that these models produce different scores and, together, they appear to cover both local dependencies and long-term trends.
2. Adaptive fusion and classification by Isolation Forest (IF): We tested a weighted fusion method, adapted to each frequency band, that combines reconstruction and forecast errors. The result is then classified using an IF. This approach avoids the rigidity of fixed thresholds and, on our data, yielded relative F1-score improvements of 6–9.5% compared to the best individual models. While absolute performance varies across frequency bands (with lower scores in high-interference bands), the consistent relative gains demonstrate the framework's robustness.
3. Operational explainability and validation on real-world data: To interpret the results, we used SHapley Additive exPlanations (SHAP) to assess the contribution of each KPI, including Handover Success Rate (HOSR), Physical Resource Block (PRB), and the number of active users. The tests were conducted on operational data spanning approximately three months and some 1,650 Evolved Node Bs (eNodeBs). In the 900 MHz band, the best observed F1 score was 0.9389, which is quite high, although performance varies across bands and indicators.

This work provides a methodological and practical basis for large-scale network anomaly detection. The approach appears applicable to real LTE operations. Adaptation to 5G is possible, but would involve validating the approach on new KPIs.

Related Work

Ensuring quality of service in an LTE network most often involves continuous monitoring of KPIs. According to the 3rd Generation Partnership Project (3GPP) (ETSI, 2022), these indicators cover accessibility, retention, mobility, and integrity. In practice, performance degradation frequently results in anomalies observed in KPI time series. These anomalies can appear in different forms: extreme point values (point anomalies); apparently normal values in an unusual context (contextual anomalies); or entire sequences of measurements that appear correct individually but form an abnormal pattern when considered together (Bordeau-Aubert *et al.*, 2023). It should also be emphasized that the diversity and complexity of these schemes make fixed-threshold methods increasingly unsuitable. They tend to either generate too many false alarms or miss more subtle degradations, according to Isaac & Sharma (2024).

Early work on automatic anomaly detection relied primarily on simple methods: Z-scores to identify extreme values; distance-based approaches such as k-NN; and clustering techniques such as DBSCAN. These tools could work well in controlled environments, but their limitations quickly appeared in practice: overly rigid distribution assumptions; difficulty scaling up; and poor performance in high dimensions (Aakula Lavanya, 2023; Chen *et al.*, 2023). More recent machine-learning models, such as IF and Support Vector Machines (SVMs), have shown better results on multidimensional KPI sets. These models generally adapt better to distribution variations than purely statistical methods. They require significant engineering effort to handle domain-specific variables. In addition, these approaches struggle to capture the temporal dependencies inherent in network performance data, a central aspect of the analysis (Chen *et al.*, 2023).

Deep learning has established itself as a benchmark for anomaly detection in time series, primarily because it can automatically extract useful representations and model complex temporal dependencies. Unsupervised approaches appear particularly relevant in this field, as operational datasets rarely contain labelled anomalies. We have two prominent families that dominate the literature.

Reconstruction-based methods: Autoencoder-type architectures learn to reconstruct normal data, and the reconstruction error then serves as an anomaly signal. Several variants exist: convolutional autoencoders (CAEs) are suited to extracting local patterns, while recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM), better model sequential dynamics (Fan *et al.*, 2023; Zou *et al.*, 2024).

Forecast-based methods: These rely on predictive models that estimate future KPI values from past observations. According to Isaac & Singh (2025), a significant deviation between expected and observed values is interpreted as an anomaly.

Some studies have turned to hybrid approaches. They combine both paradigms or explicitly integrate spatiotemporal dimensions. Jiang *et al.* (2023) combine a clustering algorithm with a BiLSTM (Bidirectional LSTM) to improve detection accuracy, while Hasan *et al.* (2024) present a framework based on a Graph Neural Network (GNN)-Transformer applied to 5G networks. These contributions open interesting perspectives, but their validation in operational conditions remains limited, as does the interpretability of the models. Table 1 categorizes the existing literature into four families and clearly contrasts them with our proposed solution to highlight the “Research Gap”.

Table 1. Comparative Analysis of Anomaly Detection Approaches in LTE RANs

Category Approach	Representative Models	Key Strengths	Research Gaps Identified
Statistical & Traditional Machine Learning	Z-score, k-NN, DBSCAN, Isolation Forest, SVM	✓ Low computational cost ✓ Adaptable to static distributions	✗ No temporal dependencies ✗ Rigid distribution assumptions ✗ Manual feature engineering
Reconstruction-based Deep Learning	Convolutional Autoencoders (CAE)	✓ Captures spatial correlations across KPIs ✓ Unsupervised learning	✗ No temporal context ✗ Treats time windows as static images
Sequential Deep Learning	LSTM, BiLSTM, RNNs	✓ Models temporal dynamics & trends ✓ Future behaviour prediction	✗ Limited inter-KPI awareness ✗ False alarms on traffic shifts
Advanced Hybrids	Transformers, GNNs, Clustering + BiLSTM	✓ High detection accuracy ✓ Global/topological dependencies	✗ Low interpretability (black-box) ✗ Small-scale/synthetic validation
Proposed Framework	CAE + BiLSTM + Transformer + Dynamic Fusion + SHAP	✓ Spatial + Temporal + Global fusion ✓ Real-world large-scale validation ✓ Explainable AI integration ✓ Reliable in noisy bands (2100 MHz)	Gaps addressed: Bridges the accuracy-trust divide for operators

Methodology

Our proposed solution is a two-stage anomaly detection framework designed to overcome the limitations of single-model approaches. The first stage generates a rich set of anomaly features using a heterogeneous deep learning ensemble. The second stage leverages these features for a more sophisticated classification, moving beyond simple error thresholding.

Dataset and Data Preparation

The preparation of the dataset represents a critical stage that directly conditions the reliability of anomaly detection in LTE RANs. The quality of subsequent analysis depends not only on the integrity of the data but also on its representativeness across frequency layers, temporal windows, and network load conditions. KPI logs inherently reflect traffic demand and radio conditions. They incorporate the operator's measurement policies, which may introduce heterogeneity and bias in the distribution of anomalies.

To ensure a valid and reproducible evaluation, the dataset was curated from operational LTE cells. It covers multiple frequency bands and extended observation periods. The raw KPI records were structured and validated, aligned across bands, standardized in units and formats, and missing values were carefully handled to preserve continuity.

Dataset description

Our analysis in this work is based on a large-scale dataset collected from Algeria's operational LTE network. The measurements cover a continuous three-month period (February 14 – May 15, 2025) and concern approximately 1,650 eNodeBs in the country's eastern region. The network operates on several frequency bands (900, 1800, and 2100 MHz). That allows us to capture heterogeneous deployment conditions, ranging from dense urban to sparsely populated rural environments. The dataset contains hourly measurements of KPIs, traditionally used to assess the quality of service. In accordance with 3GPP and International Telecommunication Union (ITU-T) recommendations, a subset of 16 indicators was selected to cover different performance aspects: accessibility, session retention, mobility, integrity, and resource utilization. Among the most representative are the E-UTRAN Radio Access Bearer (E-RAB) Drop Rate (session stability), the Inter-Frequency Handover Success Rate (mobility), the Random-Access Channel Success Rate (accessibility), the Average Channel Quality Indicator (signal quality), and the Downlink PRB Utilization (resource occupancy). The complete list is shown in Table 2. This dataset is of particular interest because it reflects the real-world complexity of a commercial LTE network. It therefore constitutes a demanding and credible testing ground for anomaly detection work.

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Table 2. Selected KPI, Their Categories, and Measured Aspects

KPI Name	What It Expresses	Unit
E-RAB Drop Rate	Proportion of established data sessions (E-RABs) that were unexpectedly dropped.	%
Intra-Freq. LTE HOSR	Handover success rate within the same LTE frequency.	%
Inter-Freq. LTE HOSR	Handover success rate between different LTE frequencies.	%
Random Access Channel (RACH) Success Rate	Success rate of random access attempts (initial connection setup).	%
Average Channel Quality Indicator (CQI)	Average Channel Quality Indicator reported by UEs, reflecting downlink channel quality.	Unitless (1–15)
Average Cell Received Signal Strength Indicator (RSSI)	Average received signal strength in a cell across all users.	dBm
User DL IP Throughput	Average downlink throughput experienced by active users.	Mbps
User UL IP Throughput	Average uplink throughput experienced by active users.	Mbps
Average DL Active User Number	Mean number of active users using downlink data per cell.	Number
DL PRB Utilization Rate	Percentage of used downlink physical resource blocks (PRBs).	%
Call Setup Success Rate (All Domains)	Percentage of successfully established calls across all domains (CS/PS).	%
RRC Establishment Success Rate	Success rate of Radio Resource Control (RRC) connection setups.	%
E-RAB Setup Success Rate	Success rate of establishing E-RAB sessions for data services.	%
4G to 3G Redirection Success Rate	Percentage of successful redirections from LTE (4G) to 3G networks.	%
RLC DL Block Error Rate (BLER) (OA)	Block error rate in the downlink Radio Link Control layer.	%
RLC UL BLER (OA)	Block error rate in the uplink Radio Link Control layer.	%

Preprocessing pipeline

To ensure reliable anomaly detection across heterogeneous frequency layers, we implemented a cohesive preprocessing pipeline designed to preserve temporal integrity and feature uniformity:

- Missing Value Management: Although missing values were rare, we applied linear interpolation to maintain strict temporal continuity. This prevents sequence-based models (such as BiLSTMs) from misinterpreting gaps as service outages (false anomalies).
- Normalization of Variables: To handle the vast scale differences between KPIs (e.g., percentages vs throughput), each variable was independently scaled to the [0,1] interval using Min-Max scaling. This ensures that the reconstruction error is driven by pattern deviations rather than variable magnitude, allowing unbiased fusion across frequency bands.

- Time Windowing: The multivariate series was divided into 7-hour sliding windows (offset by 1 hour). This duration was strategically chosen to encapsulate the full LTE "Busy Hour" cycle (typically 4–5 hours), enabling the Forecaster to model temporal trends rather than isolated point values. Simultaneously, the window is short enough to ensure the stability of spatial correlations required by the CAE, offering an optimal balance between capturing traffic dynamics and maintaining computational efficiency.
- Dataset Construction and Annotation: The dataset was split chronologically into 80% training and 20% validation. Crucially, an independent test set was constructed using data from a different *wilaya* (geographic region) not seen during training. This rigorous spatial separation tests the model's true generalization capabilities. Ground truth labels were established by network experts using operational rules and visual inspection.

Hybrid Anomaly Detection Framework

Model ensemble for feature generation

The proposed hybrid framework relies on a heterogeneous set of deep learning models. The idea is that each captures a different aspect of the network KPI time series. We have used:

- Convolutional Autoencoder (CAE) that exploits 1D convolutional layers to extract local correlations and spatial dependencies across KPIs within a fixed window;
- Bidirectional LSTM AutoEncoder (BiLSTM-AE) that learns short- and long-range temporal dependencies in both forward and backward directions, providing rich contextual representation;
- Transformer AE that employs self-attention mechanisms to capture global, long-range dependencies across the entire sequence, enabling the detection of subtle or gradually evolving anomalies;
- Bidirectional LSTM Forecaster (BiFO) for predicting future KPI behaviour, with anomaly scores derived from deviations between predicted and observed values.

Each model is trained on normal network conditions to minimize reconstruction or forecasting error. During the operational detection phase, deviations in these errors provide multiple, complementary anomaly scores. Figure 1 explicitly maps the algorithmic flow.

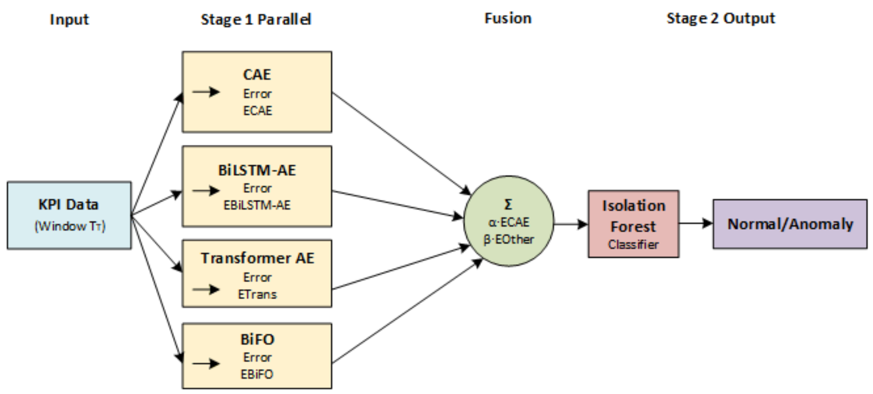


Figure 1. Proposed Hybrid Ensemble Architecture

Dynamic fusion of anomaly scores

Instead of a simple threshold applied to a model's output, a more flexible fusion strategy was chosen that combines information from several models.

$$E\_combined = \alpha\ E\_CAE + \beta\ E\_Other \tag{1}$$

where E_CAE is the baseline error from the CAE, E_Other is the error from a selected auxiliary model (BiLSTM-AE, Transformer, or BiFO), α and β are frequency-band–specific weights ($\alpha + \beta = 1$) optimized to maximize separation between normal and anomalous score distributions. This flexible fusion mechanism enables the framework to adapt across heterogeneous network conditions.

Final anomaly classification

The final step bridges the gap between the Deep Learning models and the actual decision-making using IF. Instead of simply setting a manual threshold (e.g., "if error > 0.5, then anomaly"), we treat the fused score from Equation (1) as a new input feature for the IF classifier. The process relies on a strong synergy between the two stages: (i) Deep Learning: The autoencoders and forecasters do the heavy lifting by compressing complex network behaviour into a single "error score".— a high score indicates the network is behaving unexpectedly — (ii) Isolation Forest: The IF algorithm analyses these scores to distinguish "rare" deviations from normal noise. It works on the principle that anomalies are easier to isolate than normal data points. By using IF, the system automatically learns a dynamic decision boundary. This allows it to adapt to different environments. Indeed, for example, it can distinguish between a true anomaly and the naturally higher noise levels found in the 2100 MHz band, without human intervention.

Performance Evaluation and Explainability

The performance of the hybrid framework was evaluated using standard classification metrics, including precision, recall, and F1 score. These metrics are particularly useful when the class distribution is imbalanced. To improve the model's interpretability, we used SHAP values to estimate how much each KPI influences the anomaly decision. While other methods exist, this one has become quite popular. The approach offers some transparency and can help operators understand the likely causes of detected anomalies.

Results and analysis

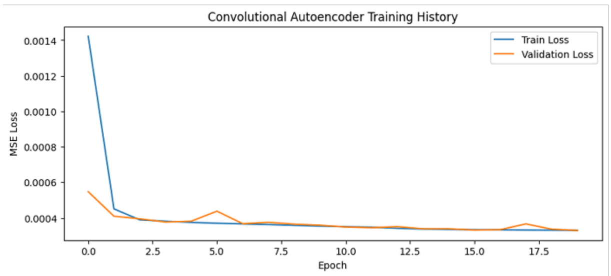
The evaluation was based on KPI time-series data from operational LTE networks across the 900, 1800, and 2100 MHz bands. The results are structured into six components: hyper-parameter tuning, individual model performance, thresholding analysis, hybrid weight optimization, IF tuning, and explainability.

Hyperparameter tuning

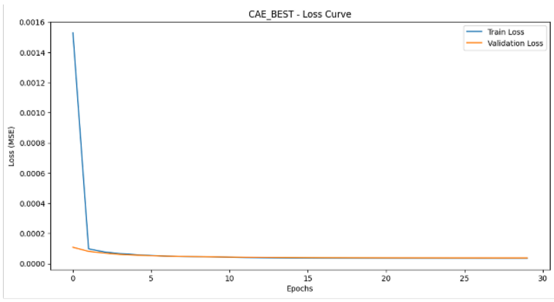
Optimization was performed using the Hyperband algorithm, minimizing the Mean Squared Error (MSE) on the validation set. This choice is mainly justified because the MSE is highly sensitive to large deviations, assigning them greater weight through the squaring of errors. We illustrate this process with the CAE (Table 3). The optimal configuration (64–32 filters, window size 7, Huber loss) significantly improved convergence and stability compared to the baseline (Figure 2).

Table 3. CAE Hyperparameter Tune Space and Selected Values

Parameter	Search Space	Selected Value
Window Size	[7]	7
Filters (Layer 1)	[16, 32, 48, 64]	64
Filters (Layer 2)	[8, 16, 24, 32]	32
Learning Rate	[1e-5, 1e-4, 1e-3, 1e-2]	1e-04
Loss Function	[MSE, MAE, Huber]	Huber
Number of Features	Fixed	16
Max Epochs	30	30



CAE Loss Curves - Before Hyperparameter Tuning



CAE MAE Curves - After Hyperparameter Tuning

Figure 2. The effectiveness of hyperparameter tuning

Equivalent optimizations were performed for BiLSTM-AE, Transformer-AE, and BiLSTM-Forecaster, with the final parameters summarized in Tables 4, 5, and 6. This ensured consistent and architecture-specific optimization prior to performance evaluation.

Table 4. BiLSTM Autoencoder Hyperparameter Configuration

Parameter	Search Space	Selected Value
Window Size	[7]	7
LSTM Units (Layer 1)	[32, 256]	224
Activation (Layer 1)	[relu, tanh, elu]	elu

Parameter	Search Space	Selected Value
Recurrent Dropout 1	[0.0, 0.5, step=0.1]	0.1
Dropout 1	[0.1, 0.5]	0.2
Add Second Layer	[True, False]	False
Final Units	[16, 128]	32
Latent Dimension	[16, 128, step=16]	48
Decoder Units 1	[32, 256, step=32]	160
Decoder Activation 1	[relu, tanh, elu]	tanh
Decoder Dropout 1	[0.1, 0.5]	0.3
Add Decoder Layer	[True, False]	True
Decoder Units 2	[16, 128]	128
Decoder Activation 2	[relu, tanh, elu]	elu
Learning Rate	[1e-5, 1e-4, 1e-3, 1e-2]	1e-03
Loss Function	[MSE, MAE, Huber]	Huber
Number of Features	Fixed	16

Table 5. Transformer AE Hyperparameter Configuration

Parameter	Search Space	Selected Value
Window Size	[7]	7
Head Size	[32, 64, 96, 128]	32
Number of Heads	[1, 2, 3, 4]	2
Feed Forward Dimension	[64, 128, 192, 256]	256
Learning Rate	[1e-5, 1e-4, 1e-3, 1e-2]	1e-04
Loss Function	[MSE, MAE, Huber]	Huber
Number of Features	Fixed	16
Max Epochs	30	10

Table 6. BiLSTM Forecaster Hyperparameter Configuration

Parameter	Search Space	Selected Value
LSTM Units	[32, 64, 96, 128]	64
Number of Layers	[1, 2, 3]	1
Dropout Rate	[0.0, 0.5]	0.1
Learning Rate	[1e-5, 1e-4, 1e-3, 1e-2]	1e-04
Loss Function	[MSE, MAE, Huber]	Huber
Number of Features	Fixed	16
Max Epochs	30	30

Baseline performance of individual models

Individual model evaluation (Table 7) shows that the CAE generally produces the highest F1 Scores (0.8835 at 900 MHz), where the F1 score is a harmonic-mean measure combining precision and recall to capture overall classification performance. The BiLSTM-AE demonstrates high precision (>0.94) but has low recall. The Transformer-AE is competitive, achieving the best PR-AUC at 1800 MHz, where PR-AUC is an evaluation metric that measures the model's ability to separate positive and negative classes. Comparison of CAE variants (Figure 3) indicates that the "Full" training approach achieves a higher Average Precision (0.78) than the incremental variant (0.66), confirming its superior ability to balance precision

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and recall. Detection delays are summarized in Table 8, revealing that full training reduces delays across all bands compared to shorter training cycles. A comparative analysis of reconstruction error distributions highlights the distinct contributions of each architecture. The CAE shows the clearest separation between normal and anomalous samples, confirming its ability to detect sharp local distortions. In contrast, the BiLSTM-AE and Transformer show a more moderate separation, with lower-magnitude errors, reflecting their focus on gradual temporal shifts and long-term contextual deviations. This diversity confirms that the models are complementary: the CAE acts as a sensitive detector for spatial spikes, while the sequence-based models identify evolving degradations, providing the statistical foundation for the hybrid fusion.

Table 7. Full Model Performance Across Frequency Bands, evaluated using Youden's J (Youden, 1950).

Band	Model	F1 Score	Precision	Recall	PR-AUC
900 MHz	CAE	0.8835	0.9885	0.7987	0.9491
	BiLSTM	0.7632	0.9894	0.6211	0.9573
	BiForLSTM	0.6294	0.9889	0.4616	0.9710
	Transformer	0.7472	0.9869	0.6012	0.9624
1800 MHz	CAE	0.8431	0.9593	0.7520	0.7776
	BiLSTM	0.7117	0.9415	0.5721	0.8110
	BiForLSTM	0.7112	0.9412	0.5716	0.8161
	Transformer	0.7839	0.9072	0.6901	0.8517
2100 MHz	CAE	0.6382	0.7519	0.5544	0.5679
	BiLSTM	0.4412	0.7705	0.3091	0.6032
	BiForLSTM	0.6722	0.7547	0.6060	0.5486
	Transformer	0.5761	0.7816	0.4562	0.5619

Table 8. Absolute Average Detection Delays

Model	Band 900 Delay	Band 1800 Delay	Band 2100 Delay
CAE	1.3937	1.8581	2.0151
BiLSTM	3.3821	3.6116	3.0726
BiForLSTM	6.0797	3.6847	1.8485
Transformer	4.0882	2.2299	2.6789

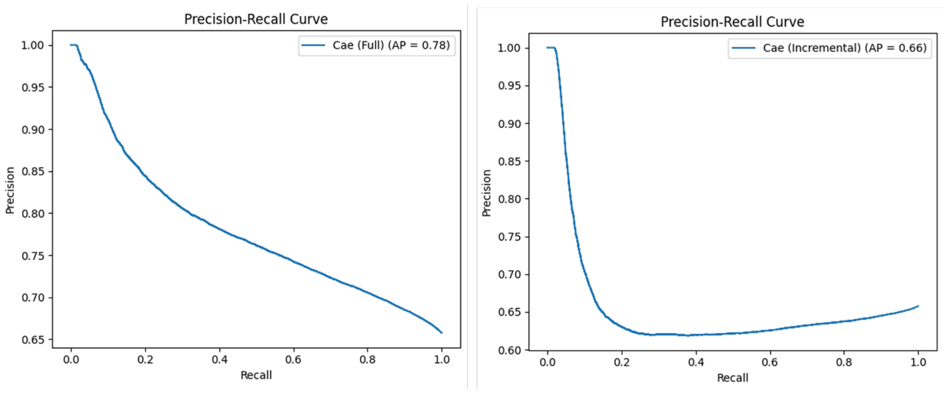

Figure 3. Comparison of PR curves for CAE in Band 2100MHz

Thresholding strategy impact

We compared three thresholding methods: classical statistical thresholding, Youden's J-statistic, and IF. The results in Table 9 indicate that IF improved recall without sacrificing precision, yielding the highest F1 Scores in most cases. On 900 MHz, CAE with IF reached 0.9362, surpassing Youden's J (0.8835). On 1800 MHz, the Transformer-AE combined with IF achieved 0.8884, compared to 0.7839 with Youden's J. While Youden's J favoured high precision (0.9894), IF delivered a more balanced trade-off.

Table 9. Thresholding Strategy Comparison for CAE and Best Other Model

Band	Model	F1 Score	Precision	Recall	PR-AUC
900 MHz	CAE (Youden's J)	0.8835	0.9885	0.7987	0.9491
	CAE (Classic)	0.9353	0.9758	0.8980	0.9491
	CAE (IF)	0.9362	0.9768	0.8989	0.9491
	BiLSTM (Youden's J)	0.7632	0.9894	0.6211	0.9573
	BiLSTM (Classic)	0.9352	0.9757	0.8979	0.9573
	BiLSTM (IF)	0.9359	0.9765	0.8986	0.9573
1800 MHz	CAE (Youden's J)	0.8431	0.9593	0.7520	0.7776
	CAE (Classic)	0.8841	0.8787	0.8895	0.7776
	CAE (IF)	0.8860	0.8806	0.8914	0.7776
	Transformer (Youden's J)	0.7839	0.9072	0.6901	0.8517
	Transformer (Classic)	0.8923	0.8870	0.8978	0.8517
	Transformer (IF)	0.8884	0.8830	0.8938	0.8517
2100 MHz	CAE (Youden's J)	0.6382	0.7519	0.5544	0.5679
	CAE (Classic)	0.7311	0.6326	0.8659	0.5679
	CAE (IF)	0.7239	0.6264	0.8574	0.5679
	BiForLSTM (Youden's J)	0.6722	0.7547	0.6060	0.5486
	BiForLSTM (Classic)	0.7295	0.6313	0.8640	0.5486
	BiForLSTM (IF)	0.7281	0.6301	0.8624	0.5486

Hybrid model performance analysis

The proposed framework combines a Convolutional Autoencoder (CAE) with auxiliary temporal models (BiLSTM-AE, BiForLSTM, Transformer-AE) by fusing their reconstruction errors and classifying the fused score with an IF. This approach avoids static thresholds and adapts to the variability in anomaly distributions across frequency bands. The experimental logic follows three steps: (i) determine optimal weightings between CAE and the auxiliary model; (ii) visualize the effect of combinations on validation performance; and (iii) validate the classification strategy and tune IF per band. The tables and figures cited below are organized to follow this exact narrative.

Weight optimization results

The relative contribution of each model is formalized by the fused score (equation (1)). To ensure consistent anomaly separability across the heterogeneous conditions of the 900, 1800, and 2100 MHz bands, we implemented a rigorous two-stage optimization procedure to determine the band-specific fusion weights (α, β).

First, we applied a Variance-to-Mean Maximization strategy. For each band, we computed the fused score across candidate α values and selected the α that maximized the variance-to-mean ratio, thereby improving anomaly separability. Second, to ensure stability, we incorporated a Balanced Weighting Rule. If the first rule produces extreme or unstable α values, we apply a balanced rule that assigns a higher weight to the model with the lower mean reconstruction error. This adaptive approach reflects the distinct physical dynamics of each layer. As shown in Table 10, temporal models dominate the fusion for the 900 MHz and 2100 MHz bands, where handling high temporal variability is critical. In contrast, the BiForLSTM dominates in the 1800 MHz band, suggesting that forecast-based deviations are more reliable than spatial reconstruction for this specific frequency.

Table 10. Best Hybrid Combinations and Performance per Frequency Band

Band	**Best Combination**	**Strategy**	**Weights (α, β)**	**Best F1-Score**
900 MHz	CAE + BiLSTM-AE	Balanced weighting	(0.069, 0.931)	0.8797
1800 MHz	CAE + BiForLSTM	Balanced weighting	(0.000, 1.000)	0.9412
2100 MHz	CAE + BiLSTM-AE	Balanced weighting	(0.251, 0.749)	0.9356

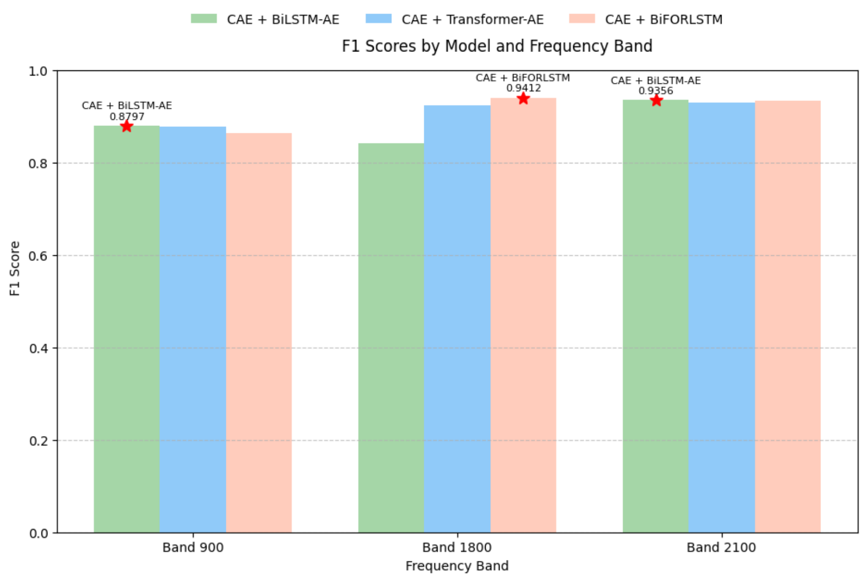

Figure 4. F1-Scores Across Model Combinations and Frequency Bands

To visualize the impact of these allocations on validation performance, refer to Figure 4, which compares the F1 curves of the evaluated combinations. It shows validation F1 curves for the main CAE+Auxiliary combinations. It confirms that weight optimization reduces score variance and stabilizes F1 on 900 and 1800 MHz, while the 2100 MHz band remains more sensitive to the chosen configuration.

Isolation Forest tuning results

Applying IF to the fused scores consistently improves detection compared with thresholding. The quantitative comparison is provided in Table 11, which reports relative F1 gains of approximately +6.3% (900 MHz), +6.5% (1800 MHz), and up to +9.5% (2100 MHz), underlining the benefit of learning a decision boundary in the fused-score space. Table 11 compares performance obtained using Youden's J and IF on the fused scores, thereby justifying replacing fixed thresholding with a learned classifier.

Table 11. Performance Comparison of Thresholding Strategies (Youden's J vs. IF) for Hybrid Model Combinations Across Frequency Bands

Band	Model	F1 Score	Precision	Recall	Improv.
900 MHz	CAE_BiLSTM (Youden's J)	0.8923	0.9885	0.8131	–
	CAE_BiLSTM (IF Scores)	0.9388	0.9794	0.9015	+5.2%
	CAE_BiForLSTM (Youden's J)	0.8836	0.9885	0.7988	–
	CAE_BiForLSTM (IF Scores)	0.9389	0.9794	0.9015	+6.3%
	CAE_Transformer (Youden's J)	0.8836	0.9885	0.7988	–
	CAE_Transformer (IF Scores)	0.9389	0.9794	0.9016	+6.3%
1800 MHz	CAE_BiLSTM (Youden's J)	0.8257	0.9590	0.7249	–
	CAE_BiLSTM (IF Scores)	0.8983	0.8928	0.9039	+8.8%
	CAE_BiForLSTM (Youden's J)	0.8431	0.9593	0.7521	–
	CAE_BiForLSTM (IF Scores)	0.8964	0.8909	0.9019	+6.3%
	CAE_Transformer (Youden's J)	0.8396	0.9598	0.7462	–
	CAE_Transformer (IF Scores)	0.8978	0.8922	0.9034	+6.9%
2100 MHz	CAE_BiLSTM (Youden's J)	0.6136	0.7531	0.5178	–
	CAE_BiLSTM (IF Scores)	0.7356	0.6365	0.8712	+19.8%
	CAE_BiForLSTM (Youden's J)	0.6382	0.7519	0.5544	–
	CAE_BiForLSTM (IF Scores)	0.7356	0.6364	0.8715	+15.2%
	CAE_Transformer (Youden's J)	0.6382	0.7519	0.5544	–
	CAE_Transformer (IF Scores)	0.7362	0.6369	0.8721	+15.3%

To ensure reproducibility, IF hyperparameters were optimized via grid search (contamination $\in \{0.10, 0.15\}$, estimators $\in \{50, 100\}$, features $\in \{0.8, 10\}$). Analysis revealed that **contamination** acts as the primary lever for robustness: raising it increases recall at the cost of precision. Consequently, a conservative rate of **0.10** was selected for the stable 900/1800 MHz bands, while the noisier 2100 MHz band required a more permissive **0.15** to effectively isolate anomalies obscured by interference, directly driving the performance gains in Table 12.

Table 12. Best IF Hyperparameters and F1-Scores per Band

Band	Best F1-Score	Contamination	n_estimators	max_features
900 MHz	0.9389	0.10	50	0.8
1800 MHz	0.8983	0.10	100	1.0
2100 MHz	0.7362	0.15	100	0.8

The final summary of net gains from the hybrid pipeline (weighted fusion + IF) compared to the best individual models is presented in Table 13. It summarizes the net benefit: optimized hybrids consistently exceed the best Stage-1 models (Youden's J/full-training), with significant F1 gains across bands and particularly pronounced improvements in weakly separable bands (2100 MHz). This table serves as the quantitative foundation for the operational argument in favour of the proposed method.

Table 13. F1 Improvement of Hybrid Models over Individual Models

Band	Indiv. (F1)	Hybrid (F1)	Best Combination	Gain (%)
900 MHz	CAE (0.8835)	**0.9389**	CAE–BiForLSTM / Transformer	6.3%
1800 MHz	CAE (0.8431)	0.8983	CAE–BiLSTM	6.5%
2100 MHz	BiForLSTM (0.6722)	0.7362	CAE–Transformer	9.5%

These results show that the hybrid framework adaptively reweights model contributions according to network conditions and consistently improves detection accuracy when paired with a carefully tuned IF. The approach attains F1-scores above 0.93 on 900 and 1800 MHz and delivers competitive performance on the more challenging 2100 MHz band. By leveraging structural complementarity between CAE and temporal models and replacing fixed thresholds with a learned decision boundary, the method provides a reproducible, operationally relevant advance in LTE RAN anomaly detection.

Model explainability and operational diagnosis

To ensure trust and transparency, we utilized SHAP to interpret the Isolation Forest's decisions. SHAP assigns a contribution value to each input feature, quantifying its impact on the classification of anomalies.

Feature Importance Hierarchy: Aggregated analysis (Figures 5 & 7) reveals a balanced contribution across KPI domains: Mobility metrics (e.g., HOSR) dominate with ~36% relative importance, followed closely by Resource Utilization (PRB, Active Users) at ~34%, and Integrity/Quality metrics at ~30%. Temporally (Figure 6), Inter-Frequency HOSR consistently displays the highest individual impact, confirming that mobility management is the primary vector for anomaly detection in this dataset.

Operational Interpretation: Crucially, these SHAP values map directly to actionable engineering diagnostics:

- High HOSR contributions signal mobility instability, often caused by neighbour list misconfiguration, weak coverage overlap, or ping-pong handovers.
- Elevated PRB and Active User values indicate congestion-driven anomalies that typically require load balancing or capacity expansion.
- RACH and RLC BLER contributions point to access failures and radio interface interference (layer-2 degradation), respectively.

By grounding anomaly scores in well-understood operational symptoms, the framework provides field engineers not just an alert but an interpretable “root cause” indicator, significantly reducing troubleshooting time.

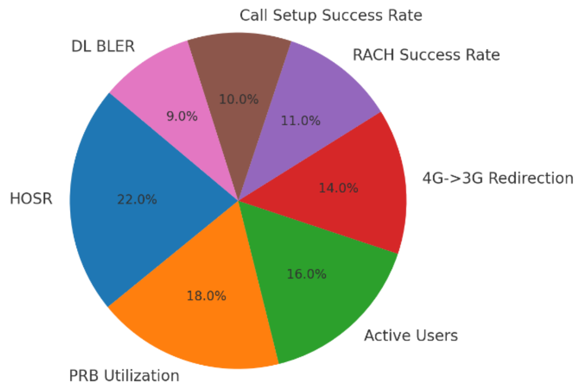

Figure 5. SHAP feature importance distribution by KPI category

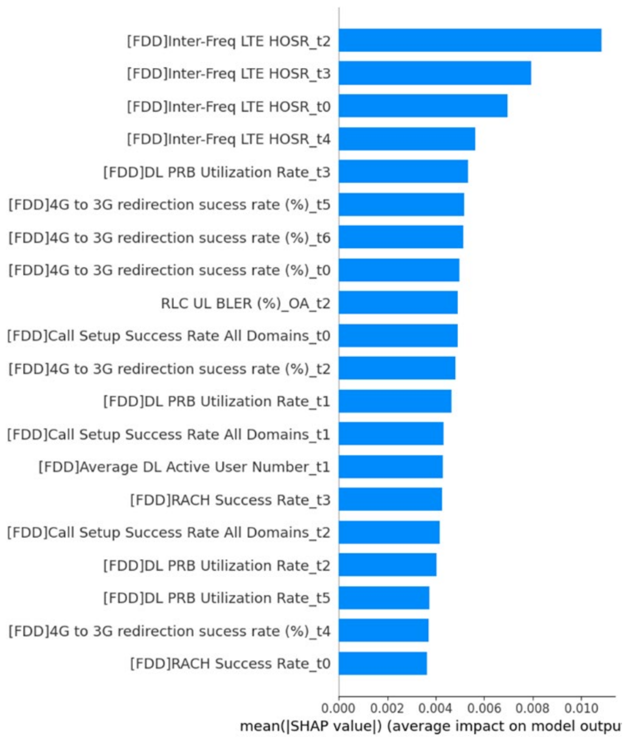

Figure 6. Individual feature SHAP values with temporal granularity

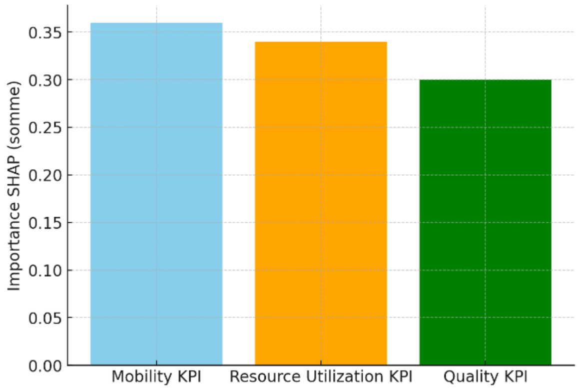

Figure 7. Aggregated SHAP importance by functional KPI domains

Discussion

This section summarizes the experimental results. It evaluates the effectiveness of the framework and its operational implications for LTE RANs. We also discuss the limitations of our work and propose avenues for future research.

Interpretation of findings

Experimental results confirm the superiority of multi-architecture fusion over single-model approaches across all frequency bands. The hybrid ensemble consistently outperformed the best individual baselines, achieving relative F1-score improvements of +6.3% at 900 MHz (vs CAE) and +6.5% at 1800 MHz. Most notably, in the challenging 2100 MHz band, the framework yielded a +9.5% gain over the best individual predictor (BiForLSTM). These results validate that fusing spatial (CAE), temporal (BiLSTM), and attention-based (Transformer) representations captures complementary anomaly signatures that isolated architectures fail to detect.

The experimental results confirm our approach: a two-stage hybrid framework detects anomalies better than isolated models coupled with a simple error threshold. The interest comes mainly from the diversity of the models and their complementarity. CAE highlights local correlations between KPIs, BiLSTM-AE better captures temporal dependencies, and Transformer appears to capture more global patterns. By combining them, we obtain a more nuanced view of network behaviour by examining the local, temporal, and global scales within a single representation space.

The second step refines the detection using the IF. Rather than analysing each model's reconstruction errors separately, the classifier appears to spot irregular patterns that are harder to see in isolation, such as small simultaneous oscillations in throughput and latency. This flexibility appears particularly useful in the 2100 MHz band, where noise and interference often obscure anomalies. These include failed handovers and sudden drops in throughput observed in this spectrum. The good results in this challenging context suggest that the framework supports heterogeneous and interference-prone environments relatively well.

SHAP analysis provides additional insight into which variables influence detection. The model's emphasis on HOSR and using PRBs in downlinks seems consistent with well-established network engineering principles. Handover failures often indicate mobility or coverage issues. Generally, a high PRB utilization rate indicates resource saturation. The variable selection is consistent with expectations in LTE engineering, lending credibility to the results.

Practical implications

Operationally, the proposed framework automates the detection of complex anomalies (e.g., mobility failures, latency spikes) and provides interpretable diagnostics via SHAP. This significantly reduces the burden of manual Root Cause Analysis and shortens the Mean Time to Repair. By shifting from reactive troubleshooting to anticipatory monitoring, the solution supports efficient network management, particularly for operators managing dense clusters with limited engineering resources. The framework's scalability, validated on large-scale operational data, confirms its readiness for production environments.

From an architectural perspective, the framework is designed to function as an intelligent inference layer within existing Operational Support Systems. It can be deployed as a containerised microservice feeding real-time anomaly scores directly into Network Management System dashboards, allowing engineers to visualize fused risk levels alongside raw KPIs. Beyond visualization, the system supports Closed-Loop Automation: high-confidence detection of specific failure modes (e.g., severe mobility degradation identified by SHAP) can trigger Self-Organizing Network modules to automatically execute remedial actions, such as neighbour relation resets or traffic steering, thereby moving operations from reactive debugging to proactive self-healing.

Limitations

Despite encouraging results, certain limitations clearly appear. The evaluation focused on a single operator, making it difficult to generalize to other contexts, such as rural or multi-provider networks. The observation period is only three months, which remains limited. In addition, hourly aggregation risks overwriting brief anomalies, for example, evening congestion or sporadic outages. Missing values were filled by linear interpolation. This choice may seem practical, but it also risks mitigating real disruptions, such as a sudden service outage. The work relied on a fixed seven-hour sliding window, without testing other granularities. It is therefore not known whether this parameter is actually suitable or what the

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model's time sensitivity is. The analysis was limited to 16 KPIs. However, other indicators, such as traffic distribution per cell or handover failure rates, could have refined anomaly detection.

Future research directions

The work is still open, and some directions are undoubtedly worth exploring. A first axis would be to improve the diagnostic module by testing adaptive learning models that can infer probable causes from history and operator feedback. This seems like a logical next step, although feasibility will depend on available data. Another direction would be to extend the study framework to 5G networks. Their performance indicators are more numerous, traffic types are more varied, and new problems arise, such as slicing management. Whether the current method is flexible enough for these environments remains to be seen. Finally, we could attempt to integrate the framework with network orchestration platforms. This would open the way to more automated resolution of anomalies through closed-loop logic.

Conclusion

This paper proposed a hybrid deep learning framework to address the inefficiencies of manual anomaly detection in Algerian LTE networks. By combining heterogeneous autoencoders with dynamic fusion and IF classification, the system achieved an F1 score of 93.89%, significantly outperforming individual baselines. The integration of SHAP provides critical interpretability, linking anomalies to actionable root causes, such as mobility failures. Future work will focus on integrating adaptive learning for automated diagnostics and extending the framework to 5G network slicing and closed-loop orchestration platforms.

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Implementing a Process Mining Framework to Improve Customer Experience

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Abstract: Improving Customer Experience (CX) is a strategic priority for organisations. This study develops and evaluates a Process Mining framework that extracts operational performance metrics and interpretable insights from event logs to support evidence-based decisions for optimizing CX. The framework encompasses the discovery of visual process models, cycle time measurement, analysis of operational flows and frequencies, identification of recurring bottlenecks, and evaluation of model accuracy. Applied to three datasets (Sepsis Events, BPI Challenge, and Hospital Billing), the results showed strong model accuracy, ranging from 88% for BPI Challenge to 100% for Hospital Billing. Additionally, the analysis uncovered efficiency variations, with cycle times spanning 19.4 hours to 149.2 days, and flagged notable delays, such as over 700 hours in administrative duties. These findings affirm the framework's ability to offer in-depth insights, helping organisations identify key obstacles and take purposeful steps to elevate service quality and customer contentment.

Keywords: Process Mining, Customer Experience, Decision Making, Performance Metrics, Process Discovery.

Introduction

In today's fiercely competitive business landscape, Customer Experience (CX) stands as a critical differentiator for generating value and fostering loyalty within service-oriented sectors. Organisations must deliver personalised and seamless interactions across multiple channels, as 56% of consumers are more likely to make repeat purchases following a personalised experience (Twilio Segment, 2023). However, managing the Customer Journey (CJ), often

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fragmented across diverse systems and touchpoints, presents a complex challenge that demands data-driven approaches.

Process Mining (PM) offers a robust suite of techniques to address this challenge, enabling the automatic discovery of real customer flows from event logs in information systems (Van der Aalst & Carmona, 2022; Van der Aalst, 2016). Unlike traditional methods, PM uncovers the complexity and diversity of customer interactions, providing a detailed view of the CJ (Dioses & Córdova, 2025). Research highlights its value in analysing omnichannel environments, identifying critical touchpoints and deviations that impact CX (Zerbino *et al.*, 2021; Halvorsrud *et al.*, 2024). Furthermore, Performance Process Mining (PPM) facilitates the quantification of key metrics, such as cycle times, delays, recurrences, and rework, which pinpoint bottlenecks and frictions in service delivery (Emamjome *et al.*, 2019; Van der Aalst, 2019). These metrics are essential for optimising processes and enhancing customer perceptions.

Moreover, several foundational process-discovery algorithms support PM applications. These include the Alpha Miner, Heuristic Miner, Fuzzy Miner, Inductive Miner, and Genetic Miner, each designed to extract process models from event data while addressing challenges such as concurrency, noise, loops, and high behavioural variability (Turdibayeva, 2024). These algorithms play a central role in enabling the discovery of underlying process structures, contributing to the accuracy and reliability of PM analyses.

Despite its potential, applying PM to CX encounters significant hurdles. Technical challenges persist, such as extracting insights from complex logs (Gal & Senderovich, 2020), which first requires pre-processing., alongside organisational barriers that impede practical adoption (Kerpedzhiev *et al.*, 2021). Moreover, it is vital to translate process transparency into improvement actions (Fleig *et al.*, 2018) and ensure the discovered model's quality to validate analyses (Van der Aalst & Carmona, 2022). However, the foremost limitation remains the absence of a tailored methodological framework for applying PM to CX analysis, a gap this research aims to address (Dioses & Córdova, 2025).

To tackle this gap, the core aim of this research is to create and test a framework that combines PM and PPM to examine and enhance CX. Specifically, this study seeks to address the following research questions:

- How can a framework guide the use of event data to measure CJ performance?
- How can insights from this framework be translated into actionable steps to improve CX?
- What is the effectiveness and accuracy of the proposed framework when applied to different datasets?

This paper is structured as follows. First, relevant literature on PM and CX is reviewed. Next, the methodology of the proposed framework is described, detailing the datasets and evaluation metrics employed. Subsequently, the results of applying the framework to case studies are presented and analysed. Then, the findings, their practical implications, and limitations are discussed. Finally, the conclusions and directions for future research are outlined.

Related Works

PM has currently gained high relevance, being integrated into various fields. This section analyses recent studies on the implications of PM.

First, in the healthcare field, research is aimed at resolving the normalisation of irregular records, correcting time zones, complementing missing information, and, through the application of algorithms such as Inductive Miner (ProM), revealing the daily oscillation of tinnitus. Likewise, under descriptive metrics, it provides the variation of case states, frequency, and average duration; altogether, these findings demonstrate the impact of applying the technique for personalised therapy delivery (Winter *et al.*, 2024). Furthermore, Split Miner is employed as a preliminary phase before feeding a model named the DREAM model, due to achieving a 2% statistical increase in AUC (Ashrafi *et al.*, 2024). While Winter *et al.* (2024) and Ashrafi *et al.* (2024) emphasise the importance of preprocessing to improve model significance, their approaches rely on dataset-specific adjustments, which hinders replication in other domains. In contrast, our framework introduces a reproducible pipeline of standardisation and cleaning, uniformly applicable to any event log, ensuring consistency and comparability.

On the other hand, CONFINE is presented as a framework that focuses on the execution of Alpha Miner within Trusted Execution Environment (TEE) enclaves to share aggregated transition matrices, ensuring General Data Protection Regulation required confidentiality (Goretti *et al.*, 2024), while discarding the feasibility of representing or optimising existing processes. The authors propose CONFINE as a framework that guarantees privacy of discovery by running in TEE environments but without addressing the optimisation or simplification of the resulting model. In contrast, our framework, in addition to being portable to secure schemes, generates consolidated diagrams and structural metrics that enable a more comprehensive operational analysis.

The reduction of process model complexity has been addressed through different alternatives, combining algorithms such as Heuristics Miner and Inductive Miner together with manual transition pruning, achieving 98% fitness (Bakhshi *et al.*, 2023). Probabilistic Inductive Miner is also incorporated to maintain 89% precision and 84% fitness (Brons *et al.*, 2021). Moreover, through the integration of meta-states, repetitive cycles are mitigated, optimising model size

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(Elkhovskaya *et al.*, 2023). Each of the techniques proposed by the authors aims to reduce model complexity, although they depend on specific parameters and manual adjustments that limit consistency across contexts. Our framework overcomes this limitation by applying constant acceptance criteria, independent of transaction volume, ensuring greater stability and reproducibility in the analysis.

For bottleneck identification, the implementation of Fuzzy Miner in the Disco process mining software (Fluxicon) reduced execution cycles by 15% and improved resource utilisation by 20% (Krajčovič *et al.*, 2024). In addition, integrating Split Miner for the reconstruction of the actual billing flow evidenced that receipts and cancellations constitute the greatest delays (Sánchez-Obando *et al.*, 2024). Recent studies on bottleneck identification have focused on shortening cycle times and pinpointing critical delay stages, often overlooking the structural quality of the underlying process model (Krajčovič *et al.*, 2024; Sánchez-Obando *et al.*, 2024). In contrast, our framework addresses this gap by combining automatic fitness and precision calculations with bottleneck detection, ensuring a robust and dependable performance analysis.

In finance, Linear Temporal Logic rules are incorporated into Rule Inductive Miner, impacting the mitigation of unauthorised transactions for users, under defined guidelines discovered from event logs, achieving 97% fitness and 94% precision (Norouzifar *et al.*, 2024). In the public sector, research focuses on shortening penalty resolution times, applying Alpha Miner to calculate penalty processing times by office, thus visualising the process flow and evaluating metrics at the levels of precision and simplicity (Jlidi *et al.*, 2024) However, certain studies in specific domains like finance and the public sector do not embed temporal indicators directly into the graph, nor do they explicitly highlight bottlenecks disrupting process flow (Norouzifar *et al.*, 2024; Jlidi *et al.*, 2024). Our framework overcomes this drawback by weaving time and frequency metrics into the unified diagram, enabling a more thorough and visually cohesive operational review.

Across all reviewed works, the relevance of PM in different sectors is confirmed; however, critical gaps persist related to the difficulty of interpreting discovered models, the lack of consistent mechanisms to synthesise variants, and the absence of operational indicators integrated into graphs that allow bottlenecks to be highlighted and improvements to be proposed. Our framework addresses these limitations by generating a consolidated and easily readable diagram, maintaining uniform synthesis criteria, and overlaying temporal and frequency metrics directly into the flow, thus facilitating a more understandable analysis oriented toward the practical optimisation of processes.

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Methodology

In PM, algorithms such as Inductive Miner, Split Miner, and Heuristics Miner enable the discovery of models from event logs; however, they often produce complex diagrams, sensitive to parameter settings and lacking integrated operational metrics. To directly address these limitations, in this study we developed a methodological framework implemented in Python. The rationale behind this approach was to create a method that ensures the generation of process models that are visually clean, reproducible, and directly enriched with the essential performance metrics for CX analysis.

All datasets utilised in this study were obtained from open-access repositories and consist of event logs captured by an Enterprise Resource Planning (ERP) system. Covering the period from 2012 to 2017, each log differs in data volume and attribute composition, reflecting varied operational contexts within healthcare and administrative domains. The primary characteristics of the three event logs — Sepsis Events, BPI Challenge, and Hospital Billing — which enable CX-focused process analysis, are detailed in Table 1.

Table 1. Summary of the Datasets Used

Name	Domain	Brief description	Transactions
Sepsis Events	Healthcare (Clinical/ Emergency)	Trajectory log of sepsis patients in a Dutch hospital	1,050
BPI Challenge	Finance (Loan applications)	Event log of a loan-application process	13,087
Hospital Billing	Healthcare (Administrative/ Finance)	ERP event log for medical-service billing; anonymised, random sample	100,000 (three-year sample)

The three chosen datasets—Sepsis Events (clinical), BPI Challenge (financial), and Hospital Billing (administrative-health)—were selected for their domain diversity, size, and features to test the framework's applicability across varied contexts. Notably, Hospital Billing includes anonymised data, preserving only relative time intervals.

For analysis, each log was organised using the three core attributes for process mining: case identifier (case), activity name (event), and timestamp (start-time).

Data preprocessing comprised three key stages: first, converting case identifiers to text format for standardisation; second, filtering to retain only cases beginning with the process's most frequent event; and third, adjusting timestamps to minute-level precision to avoid segmentation conflicts.

To enhance case standardisation and refine flow structure, two artificial "start" and "end" nodes were added to each case to improve segmentation, integrated into the dataset based on the sequence's start and end times.

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To construct the process model, the “base case” was defined as the route with the greatest number of unique events. The flow visualisation, depicting activities as linked nodes, was produced using Python’s Graphviz library. Parallel activities (concurrency) were then detected by grouping events according to their timestamps.

Following parallel event identification, logical gates were introduced to reflect their connections. These include “AND-Split” and “AND-Join” to depict parallelism, and “OR” gates for parallel events, based on the frequency of recorded transitions.

As the model takes shape, transactions are incorporated into the base path, with recurrence patterns assessed to determine the optimal event position — considering the most frequent preceding and succeeding events to maintain flow consistency.

A key feature of the diagram is its emphasis on event frequency. Additionally, it uses a colour scale (red for high frequency, green for low) to display activity volume, enabling end users to quickly spot high-demand tasks for better resource allocation.

Once the visual process flow model is finalised, the framework advances to the generation and export of results. The complete framework schema is detailed in Figure 1.

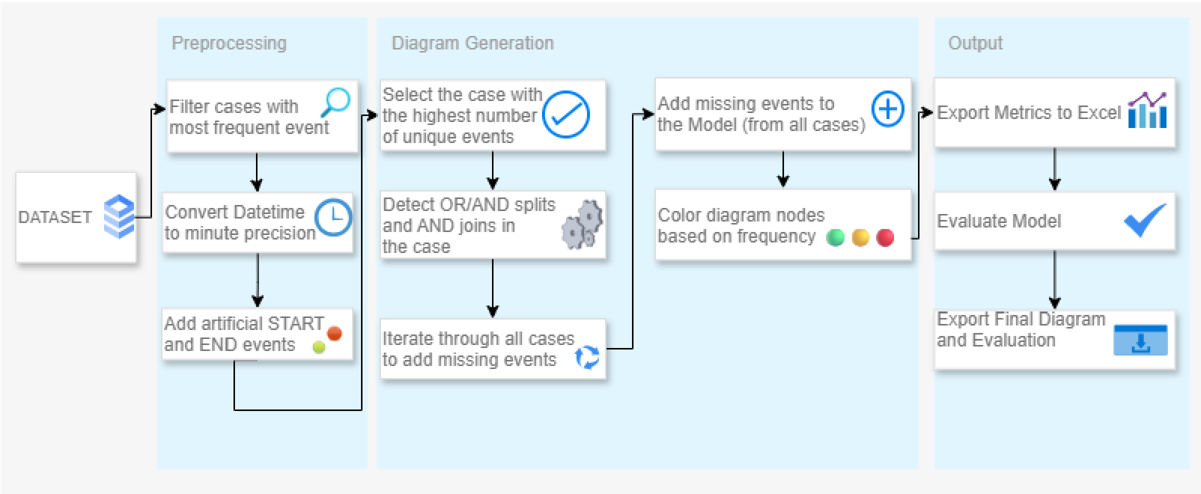

Figure 1. Architecture of the developed Process Mining framework

Results

This section presents the findings from applying the proposed framework to three datasets: Sepsis Events, BPI Challenge, and Hospital Billing. It explores process performance (encompassing times, flow, and bottlenecks) along with the accuracy of the generated models, all considered through the perspective of CX.

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Analysis of the identified model's accuracy

The quality of the discovered models was assessed using the Precision metric, which gauges how closely the model reflects real-world behaviour in the data. Table 2 shows the detailed outcomes for the three distinct datasets.

Table 2. Model Precision Results by Dataset

Dataset	Precision Achieved
Sepsis Events	95%
Hospital Billing	100%
BPI Challenge	88%

The findings highlight the framework's strong reliability. It achieved perfect accuracy (100%) with Hospital Billing and a highly robust 95% with Sepsis Events. The 88% score for BPI Challenge remains impressive, given the significant variability typical of this process. These figures are crucial, as they confirm that the subsequent performance analysis rests on a trustworthy depiction of the CJ.

Discovered Process Models by the framework

A key outcome of the framework is the creation of visual process flow models for each dataset, developed using the outlined methodology. These models are presented and described below.

Discovered Process Model for Sepsis Events

Figure 2 depicts the patient care flow for sepsis cases. The process begins with a standard Emergency Room (ER) Registration, followed by parallel triage steps (ER Triage and ER Sepsis Triage).

A prominent pattern is the frequent loop between Leucocytes (2138) and CRP (2070) tests, marked in red, indicating a repetitive monitoring cycle. While clinically essential, this loop may contribute to extended waits and patient anxiety.

The model also uncovers multiple low-frequency exit paths, such as various releases (Release B, C, D, E) and admissions (Admission NC, IC). Though their rare occurrence minimises their effect on overall performance metrics, the wide variety of these paths points to a lack of standardisation in the final stages, potentially leading to inconsistent CX.

Discovered Process Model for BPI Challenge

The model for the BPI Challenge (Figure 3) illustrates a complex loan application flow, beginning with 13,087 instances at START. The process starts with a structured linear sequence (A_SUBMITTED and A_PARTLYSUBMITTED, both with 13,087 occurrences), but soon branches into diverse back-office administrative tasks (prefixed with 'W_'), where operational complexity peaks. In contrast, minor flows like application cancellation (A_CANCELLED, 2807 occurrences) play a limited role in the overall process but hold significance for a specific group of clients.

The dominance of administrative phases is clear in high-frequency nodes, such as 'W_Completeren aanvraag', highlighted in red on the diagram. The most striking insight, however, is the presence of self-loops (cycles) in this and other tasks, like 'W_Nabellen offertes'. Far from trivial, these loops indicate rework, iterative checks, or follow-ups, directly contributing to inefficiency and a poor CX through uncertainty and prolonged waiting times.

Discovered Process Model for Hospital Billing

The diagram for Hospital Billing (Figure 4) portrays a billing process that begins on a large scale with the NEW activity (14,175 occurrences). A clear high-frequency main flow emerges, progressing through FIN (10,344), RELEASE (10,142), CODE OK (9,833), and BILLED (9,542). However, the model uncovers two significant deviations. First, a highly frequent alternative path involves altering a diagnosis via CHANGE DIAGN (6,569 occurrences), indicating substantial rework that affects nearly half the case before billing concludes.

Second, several low-frequency exception routes (green nodes) such as CODE NOK (336), MANUAL (67), and STORNO (549), are evident. Though these minor flows do not sway average performance metrics, they hold critical importance from a CX perspective. They pinpoint exact failure points, highlighting cases needing costly manual intervention and cancellations—each marking a negative, challenging experience for the end customer.

Quantitative analysis of process performance

The framework extracted key performance metrics for each dataset, focusing on cycle times, flow, bottlenecks, and activity durations, with interpretations of their potential impact on CX.

Cycle times

For the Sepsis Events dataset, the median cycle time was 5.6 days. The histogram (Figure 5) indicates that most cases (537) are resolved within 29 days. Yet, the distribution is notably skewed: the average of 28.9 days is five times the median, driven by a "long tail" of cases with unusually long durations, reaching 95 days (P90) and even 161 days (P95).

From a CX standpoint, this variability is significant. It suggests that, while most patients encounter a predictable journey, a notable group faces extreme delays, exposing a clear inconsistency in service delivery.

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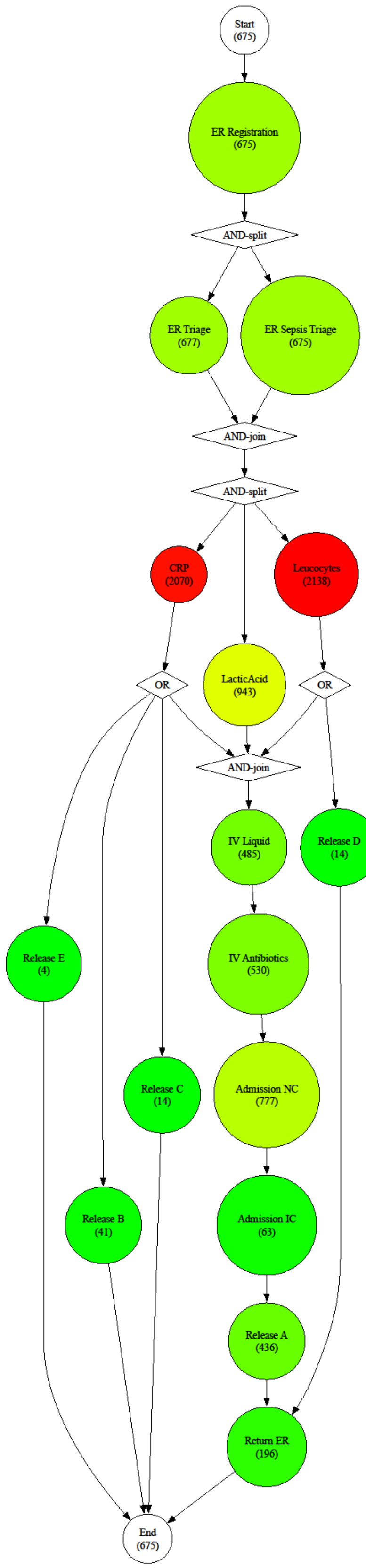
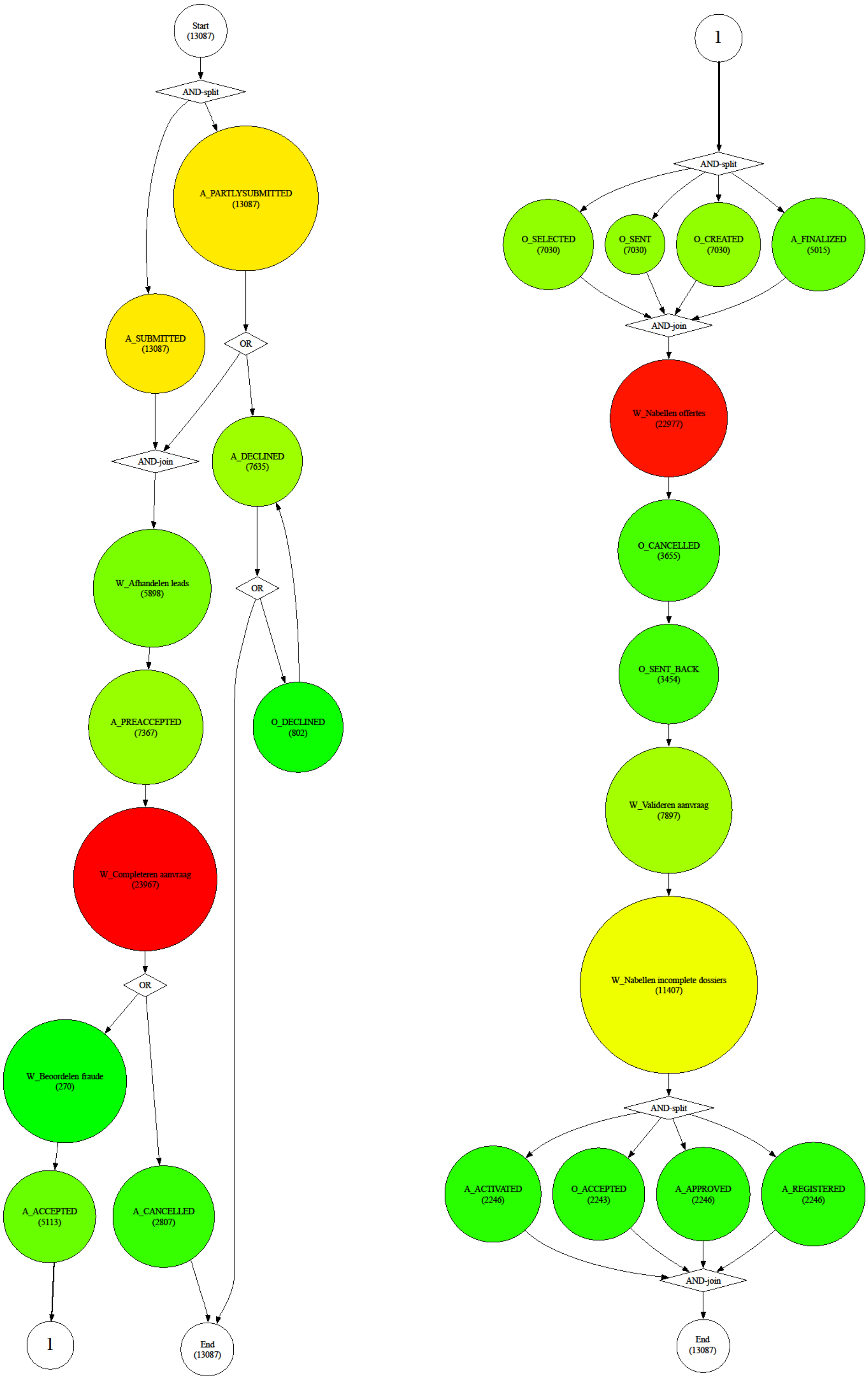


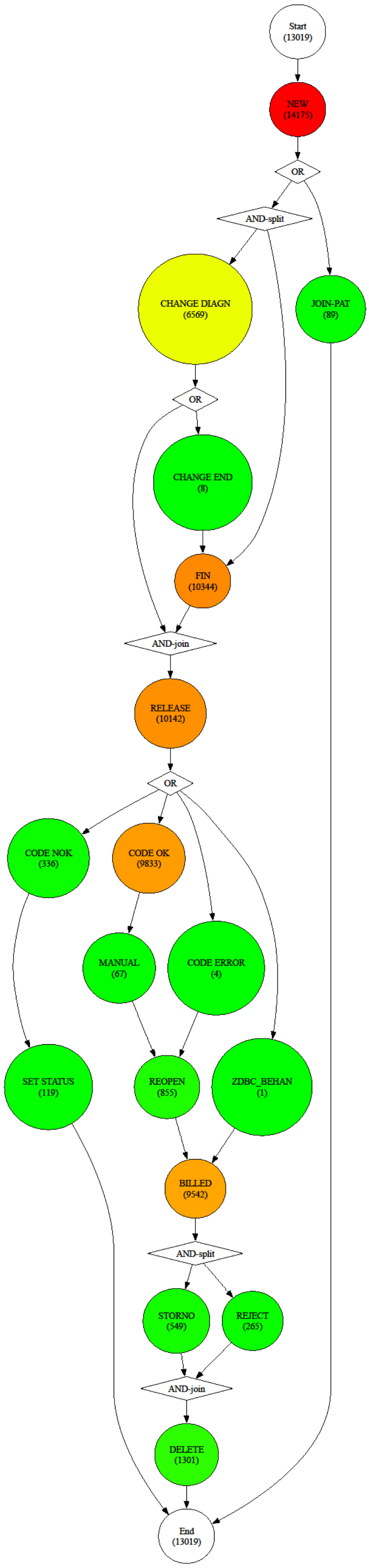
Note: Nodes depict process activities. Colour coding reflects frequency: red indicates high frequency, while green denotes low frequency. Diamond-shaped gates structure the flow, representing parallelism (AND) or decision points (OR)

Figure 2. Process Flow Diagram – Sepsis Events



Note: Nodes depict process activities. Colour coding reflects frequency: red indicates high frequency, while green denotes low frequency. Diamond-shaped gates structure the flow, representing parallelism (AND) or decision points (OR).

Figure 3. Process Flow Diagram – BPI Challenge



Note: Nodes depict process activities. Colour coding reflects frequency: red indicates high frequency, while green denotes low frequency. Diamond-shaped gates structure the flow, representing parallelism (AND) or decision points (OR).

Figure 4. Process Flow Diagram – Hospital Billing

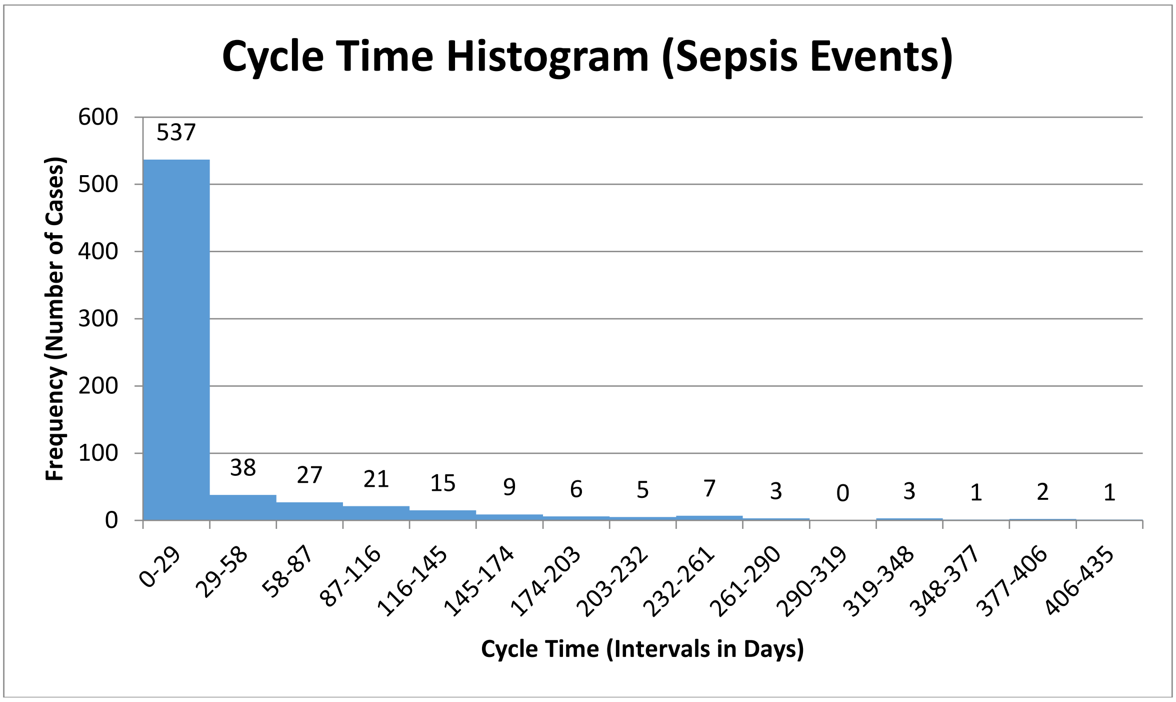


Figure 5. Cycle Time Distribution (Days) for the Sepsis Events dataset

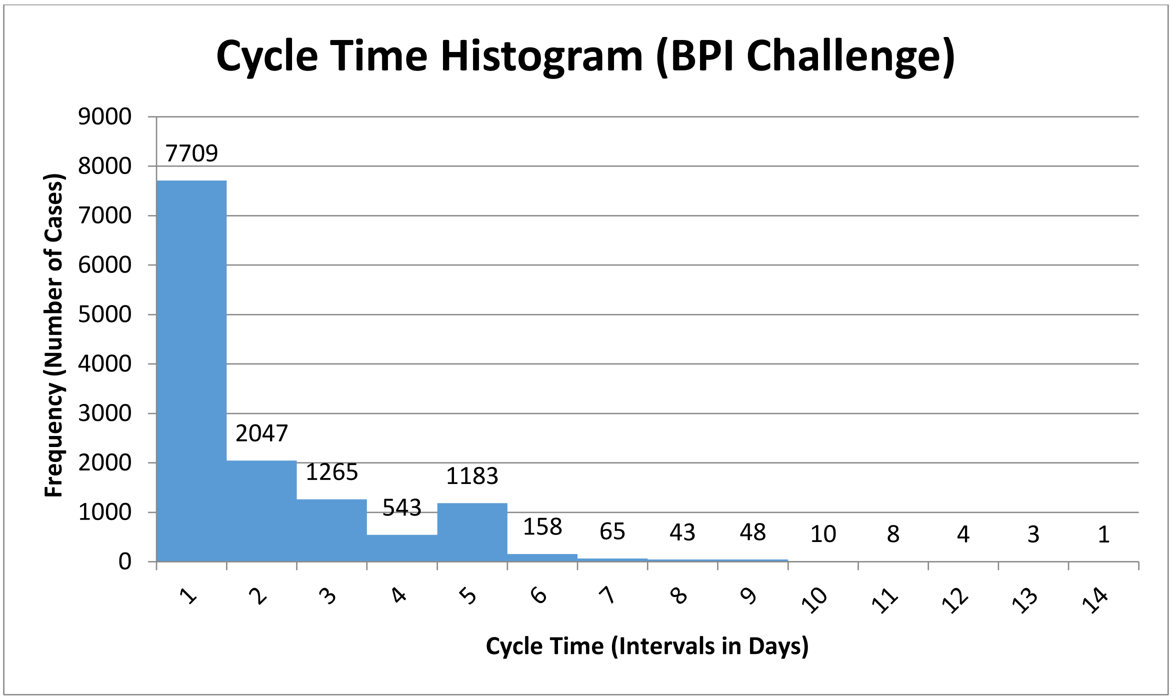


Figure 6. Cycle Time Distribution (Days) for the BPI Challenge dataset

In contrast, the BPI Challenge process proved notably faster, with a median cycle time of 19.43 hours. The histogram (Figure 6) shows that most cases (7,709) fall within the first week. Nevertheless, like Sepsis, a "long tail" emerges: the gap between the median and the average (43.71 hours), along with the P90 (112.25 hours) and P95 (171.01 hours) percentiles, highlights a subset of cases with significantly longer durations.

In a competitive setting like loan applications, this inconsistency severely impacts CX. It creates an unpredictable journey, where a minority of applicants endure prolonged uncertainty, increasing the likelihood they may abandon the process and turn to a competitor.

Lastly, the Hospital Billing process exhibited the longest cycle time, with a median of 149.2 days. Its histogram (Figure 7) highlights a key trait: a bimodal distribution. This pattern points to two dominant subprocesses, one resolving cases within 70 days (3,498) and another, of comparable size, taking between 140 and 210 days (3,654).

This duality signals a highly inconsistent CX. Furthermore, the process's "long tail," with 5% of cases exceeding 382 days (P95), reflects serious shortcomings that negatively affect both patient satisfaction and the hospital's revenue cycle.

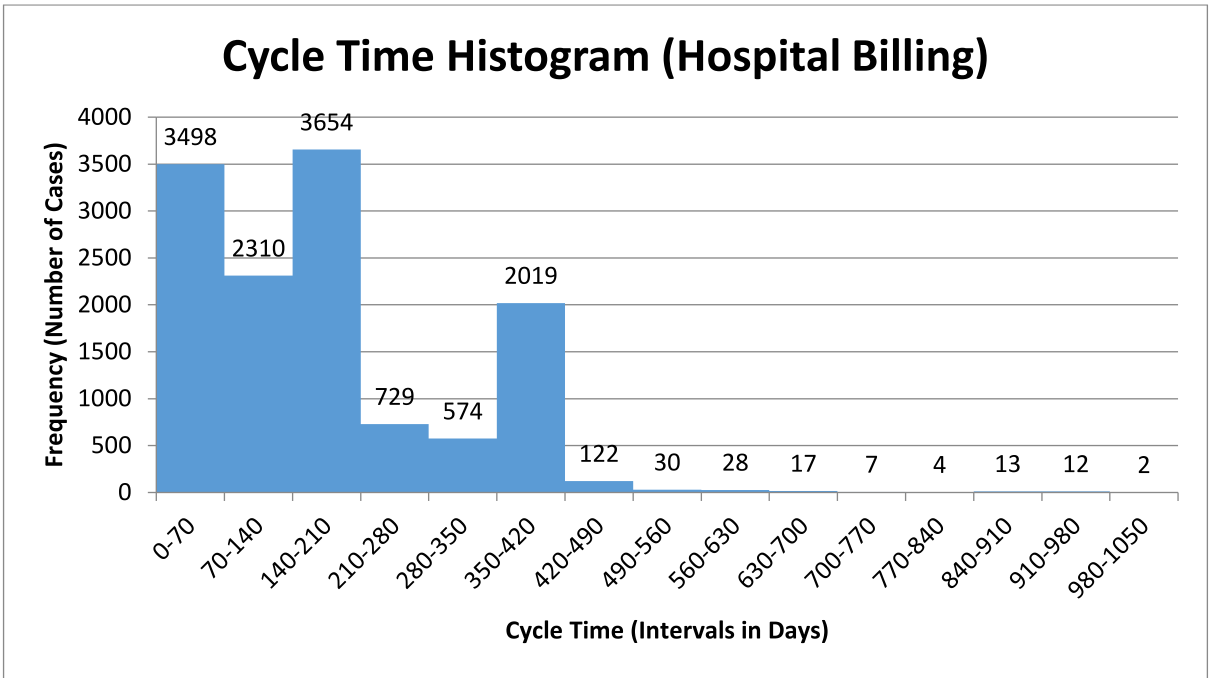


Figure 7. Cycle Time Distribution (Hours) for the Hospital Billing dataset

These substantial differences in overall process cycle times and the shapes of their distributions, clearly visible in the histograms and quantified in Table 3, are critical from the perspective of CX and operational efficiency.

Table 3. Descriptive Statistics of Total Cycle Time by Dataset

Dataset	Median (Days)	Average (Days)	P90 (Days)	P95 (Days)	Maximum (Days)	Cases
Sepsis Events	5.61	28.88	94.98	161.12	422.33	675
BPI Challenge	0.81	1.82	4.68	7.13	43.46	13087
Hospital Billing	149.25	165.78	374.10	382.92	1035.42	13019

Note: P90 and P95 refer to the 90th and 95th percentiles, respectively. For BPI Challenge, the median is 19.43 hours, and the average is 43.71 hours.

Collectively, these findings uncover three distinct failure patterns in CX. The Sepsis process stands out for its extreme inconsistency, marked by a 'long tail' that signals unpredictable service. The BPI Challenge, while faster, shows variability that breeds uncertainty and raises the risk of customer drop-off. Lastly, the bimodal distribution of Hospital Billing proves most telling, hinting at a core lack of standardisation that results in two sharply contrasting CXs.

Flow and frequency analysis

This section highlights the most common process routes and the highest-frequency activities across each dataset. The analysis targets two key areas: the most recurring transitions between activities; and the frequency of individual tasks.

Sepsis Events

Table 4 presents the three most frequent direct transitions between operational activities, revealing the predominant workflows in the management of sepsis patients.

Table 4. Most Frequent Transitions (Top 3) - Sepsis Events Dataset

Rank	Origin	Destination	Frequency
1	Leucocytes	CRP	1102
2	CRP	Leucocytes	919
3	Start	ER Registration	675

As shown in Table 4, the dominant pattern is the high-frequency cycle between Leucocytes and CRP tests (transitions 1 and 2). This quantitative finding supports the iterative monitoring observed in the visual process model.

From a CX viewpoint, this loop emerges as a critical concern, reflecting "test and wait" cycles that may prolong patient stays and foster uncertainty. The third most frequent transition (Start -> ER Registration, 675 occurrences) merely reinforces the standardised entry point to the process.

To enhance the flow overview, Table 5 highlights the most common individual activities, validating the earlier flow patterns and shedding light on the process's operational focus.

Table 5:Most Frequent Operational Events (Top 3) - Sepsis Events Dataset

Rank	Event	Absolute Frequency	Percentage Usage (%)
1	Leucocytes	2138	19.28%
2	CRP	2070	18.67%
3	Lactic Acid	943	8.50%

Note: The usage percentage refers to the total events recorded in the log, rounded to two decimal places.

The data indicate that the process is overwhelmingly led by the diagnostic phase. Leucocytes tests (19.28%) and CRP (18.67%), part of the monitoring loop, account for nearly 40% of all recorded activities. This focus on diagnostics, bolstered by a third common test like Lactic Acid (8.50%), directly shapes CX by framing the patient journey as a repetitive cycle of awaiting results.

BPI Challenge

The BPI Challenge flow analysis uncovers a process heavily influenced by self-loops in key administrative stages. As detailed in Table 6, the most frequent transitions, by a wide margin, involve iterations on 'W_Completeren aanvraag' (16,469) and 'W_Nabellen offertes' (15,314).

Table 6. Most Frequent Transitions (Top 3) - BPI Challenge Dataset

Rank	Origin	Destination	Frequency
1	W_Completeren aanvraag	W_Completeren aanvraag	16469
2	W_Nabellen offertes	W_Nabellen offertes	15314
3	Start	A_SUBMITTED	13087

Note: Activity names such as 'W_Completeren aanvraag' and 'W_Nabellen offertes' denote administrative phases.

Table 7 underscores this observation, revealing that these two activities alone make up nearly 25% of all operational work. These loops go beyond mere pauses; they signify rework and persistent follow-ups, serving as the primary drivers of bottlenecks and cycle time inconsistencies. For applicants, this equates to a frustrating "administrative limbo", where their request stalls, heightening the chance of dropping out.

Table 7. Most Frequent Operational Events (Top 3) - BPI Challenge Dataset

Rank	Event	Absolute Frequency	Percentage Usage (%)
1	W_Completeren aanvraag	23967	12.57%
2	W_Nabellen offertes	22977	12.05%
3	A_SUBMITTED	13087	6.86%

Note: The usage percentage refers to the total events recorded in the log. 'Start' and 'End' are excluded from the operational ranking. A_PARTLYSUBMITTED shares the same frequency as A_SUBMITTED.

Hospital Billing

The flow analysis of Hospital Billing uncovers a split process with two prominent high-frequency pathways. On the one hand, Tables 8 and 9 highlight a clear "happy path" marked by a straightforward sequence—FIN -> RELEASE -> CODE OK—supported by the high occurrence of these activities (NEW, FIN, RELEASE rank as the top three).

On the other hand, rivalling in volume, a significant rework pathway emerges through 'CHANGE DIAGN' (6,130 occurrences). The recurring nature of this correction activity points to systemic issues in the initial data collection. For customers, this rework directly leads to delays, potential billing errors, and an overall experience marked by uncertainty and mistrust.

Table 8. Most Frequent Transitions (Top 3) - Hospital Billing Dataset

Rank	Origin	Destination	Frequency
1	Start	NEW	13019
2	FIN	RELEASE	9947
3	RELEASE	CODE OK	9705

Table 9. Most Frequent Operational Events (Top 3) - Hospital Billing Dataset

Rank	Event	Absolute Frequency	Percentage Usage (%)
1	NEW	14175	15.71%
2	FIN	10344	11.46%
3	RELEASE	10142	11.24%

Note: The usage percentage refers to the total number of events recorded in the log. 'Start' and 'End' are excluded from the operational ranking.

Analysis of average times between events and potential bottlenecks

This section pinpoints bottlenecks by examining two key metrics for each event: the average elapsed time and the percentage of cases exceeding that average. Leveraging both metrics helps differentiate delays stemming from atypical cases from those reflecting broader, systemic slowness.

Sepsis Events

Table 10 presents the three events with the highest average waiting and duration times, highlighting potential bottlenecks in the sepsis patient care process.

Table 10. Events with the Highest Average Time Between Events and % of Cases Exceeding the Average - Sepsis Events Dataset (Top 3)

Rank	Event	Average Time (Approx. Days)	% Cases > Average
1	Return ER	~79.3	37.8%
2	Release C	~5.8	28.6%
3	Release D	~4.4	35.7%

Note: Average time (waiting + duration) associated with the completion of the listed event. % Cases > Average indicates the proportion of instances where the event occurred and exceeded its own average time.

The 'Return ER' activity stands out with an exceptionally long average duration of approximately 79.3 days, its slowness posing a widespread issue that impacts 37.8% of cases passing through it. From the patient's perspective CX, this bottleneck embodies the worst-case scenario: a serious relapse necessitating an extended re-evaluation period. Delays in discharge activities (Release C and D) further highlight inefficiencies that extend hospital stays and heighten patient uncertainty.

BPI Challenge

For the BPI Challenge dataset, the data in Table 11 quantify the impact of the administrative loops identified earlier.

The activity ‘W_Nabellen offertes’ (~75.3 hours), involving offer follow-ups, emerges as the primary bottleneck. For customers, this wait exceeding three days creates a critical friction point, fostering uncertainty and raising the risk of abandonment. Notably, the analysis clarifies the nature of the delays: the issue in ‘W_Valideren aanvraag’ is more widespread (29.1% above average), whereas in ‘W_Completeren aanvraag’ it appears tied to atypical cases (7.3% above average).

Table 11. Events with the Highest Average Time Between Events and % of Cases Exceeding the Average - BPI Challenge Dataset (Top 3)

Rank	Event	Average Time (Approx. Hours)	% Cases > Average
1	W_Nabellen offertes	~75.3	20.9%
2	W_Valideren aanvraag	~31.4	29.1%
3	W_Completeren aanvraag	~21.3	7.3%

Note: Average time (waiting + duration) associated with the completion of the listed event.

Hospital Billing

In the Hospital Billing process, bottlenecks are critically concentrated in the final stages of closure and billing (Table 12).

Table 12. Events with the Highest Average Time Between Events and % of Cases Exceeding the Average - Hospital Billing Dataset (Top 3)

Rank	Event	Average Time (Approx. Days)	% Cases > Average
1	FIN	~129.2	26.3%
2	SET STATUS	~63.4	13.4%
3	BILLED	~55.6	38.5%

Note: Average time (waiting + duration) associated with the completion of the listed event.

Activities such as FIN (~129 days) and BILLED (~56 days) contribute to months of delay, hinting that cases slip into an “administrative limbo” after clinical service. For the hospital, this signals a severely delayed revenue cycle. For patients, it results in a poor experience, receiving bills months late, which breeds confusion and mistrust.

Discussion

The findings of this study confirm that the proposed framework generates visually clear and quantitatively reliable process models from complex event logs. The high accuracy across the three datasets (88%–100%) assures that the models faithfully mirror real workflow patterns, providing a sturdy foundation for analysis. The framework effectively identified execution patterns and bottlenecks with clear CX implications, such as monitoring cycles (Sepsis), administrative rework (BPI Challenge), and bifurcated processes (Hospital Billing).

When viewed against existing literature, our work brings forth multiple contributions. In the realm of complexity reduction, research has shown that high-fidelity models can be achieved by blending algorithms with manual adjustments (Bakhshi *et al.*, 2023; Brons *et al.*, 2021). Our results extend this by proving that similar precision levels (88%–100%) are attainable through a standardised pipeline, free of intricate tuning, reinforcing that simplicity and reproducibility can coexist with accuracy.

On bottleneck identification, some studies succeed in cutting cycle times and spotting delay stages but often neglect the underlying model's structural quality (Krajčovič *et al.*, 2024; Sánchez-Obando *et al.*, 2024). Our approach builds on this by merging bottleneck analysis with simultaneous model quality assessment. Likewise, domain-specific studies have largely focused on process flow visualisation (Norouzifar *et al.*, 2024; Jlidi *et al.*, 2024). Our framework progresses further by overlaying performance metrics (like frequency via colour coding) onto the graph, turning it into a visual diagnostic tool.

Finally, the framework's effectiveness across diverse domains stands apart from preprocessing approaches that rely on dataset-specific tweaks, which can hinder replication (Winter *et al.*, 2024; Ashrafi *et al.*, 2024). Our standardised pipeline, however, proves robust and adaptable, affirming its potential as a generalisable analytical tool.

From a practical angle, the framework yields insights that guide specific managerial actions. For the excessive cycle times in Hospital Billing, a prompt step could involve assembling a cross-functional team (finance, admissions, IT) to probe the process split's causes and explain why half the cases lag months behind the rest. To tackle self-loops in BPI Challenge, a manager might run a process mapping workshop (value stream mapping) with the administrative team to uncover root causes of rework, then prioritise simplification or automation. In Sepsis Events, the testing cycles signal a need for clinical leadership to audit care protocols against best-practice guidelines, seeking optimisation chances without risking patient safety.

Conclusions

This study successfully developed and tested a PM framework to derive performance metrics and actionable insights aimed at enhancing CX, proving its relevance across three diverse datasets (Sepsis Events, BPI Challenge, and Hospital Billing). The framework produced visual process models (Figures 2, 3 and 4) with high accuracy (88%–100%, Table 2), forming a solid base for comprehensive quantitative analysis.

Key findings, discussed earlier, encompass the significant variation in process durations and their direct impact on CX, alongside the detection of flow patterns (cycles, self-loops) and slow phases that highlight inefficiencies or critical points affecting CX. The framework's consistent application to varied datasets underscores its robustness and potential for broad use.

Despite its practical value, the framework reveals key limitations with direct implications. First, its generalisability is restricted; validated in health and finance domains, its use in other sectors (e.g., manufacturing) would necessitate a preliminary validation to ensure reliability. Second, its quantitative focus accurately identifies where bottlenecks occur but not always the underlying why, often requiring complementary qualitative analysis.

Moreover, while the models boast high accuracy, they do not reach 100% across all datasets due to "scattered activities" or infrequent process variants. The current framework prioritises uncovering the main flow over representing all exceptional cases.

Looking ahead, this study opens several research avenues to expand the framework. First, integrating qualitative data, such as satisfaction surveys (CSAT) or Net Promoter Score (NPS), could link quantitative bottlenecks to actual customer perceptions. Second, adding predictive elements with machine learning models might forecast real-time risks of significant delays in active cases. Finally, refining modelling with advanced variant analysis techniques could capture not just the main flow but also exception routes critical to CX.

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Text Mining Applications for Mobile Banking User Satisfaction

A Systematic Literature Review

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Abstract: As mobile banking gains popularity for financial transactions, research aimed at enhancing user satisfaction has become increasingly important. This paper examines the literature on the application of text-mining methods to extract insights from user-generated content in the context of mobile banking. The objective is to identify the text-mining methods commonly employed and the key factors influencing user satisfaction in mobile banking. A systematic literature review was conducted to identify relevant articles from Google Scholar, Scopus, IEEE Xplore, and ScienceDirect. The results show that sentiment analysis, topic modelling and word cloud are the most widely used methods in the mobile banking context. Furthermore, the findings highlight that the most cited drivers of user satisfaction in mobile banking based on text mining approaches are security, ease of use and software updates. Additionally, the review uncovers gaps in previous research, particularly the underutilization of advanced text mining methods. To address these gaps, this paper establishes a comprehensive framework that consolidates previous findings and provides actionable recommendations for future research. This framework serves as a guide to better understand user satisfaction and to leverage text mining for more effective insights in the evolving landscape of mobile banking.

Keywords: Mobile banking, text mining, user satisfaction, artificial intelligence, literature review.

Introduction

The rise of mobile banking (M-Banking) has completely changed the way banking services are provided, by enabling consumers to manage their accounts and conduct financial transactions from the comfort of their smartphones (Falaiye *et al.*, 2024). User reviews on social media and

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mobile application platforms are essential for understanding the key factors driving customer satisfaction (Maulana *et al.*, 2024). These reviews provide real-time feedback on user experiences, offering valuable insights into service quality, emerging trends, and areas that need improvement. The interactive nature of social media allows users to openly express their expectations and frustrations, making these platforms rich sources for extracting insights into satisfaction determinants. However, the rapid rise of mobile applications has led to a huge number of user reviews spread across different platforms. These reviews are often unstructured and too large to analyse manually. To solve this, big data methods are used to extract useful insights from this information. Text mining, a key method in big data analytics, automates the process of analysing these reviews (Pejić Bach *et al.*, 2019). Text mining is the process of analysing large collections of documents to uncover new insights or address specific research questions (Abdusalomovna, 2023). Topic modelling, which identifies major topics in the text, and sentiment analysis, which identifies attitudes and feelings, are examples of common methods. These methods are frequently used to evaluate and extract knowledge that aids companies in enhancing their services. In fact, text mining methods have been extensively applied in analysing user reviews for mobile applications, particularly in areas such as mobile banking (Balcıoğlu, 2024), e-commerce (Suprayogi *et al.*, 2018), healthcare (Biswas *et al.*, 2021), social media analysis, customer relationship management, and business intelligence (Sfoq *et al.*, 2024).

As M-Banking applications (apps) continue to grow, one of the primary goals for developers in financial institutions is to ensure that users are satisfied with their experience. Nevertheless, understanding the elements that affect user satisfaction, especially from the viewpoint of the user, is critical. One useful technique for gaining information on how users interact with these apps is text mining, especially when it is applied to user reviews (Krishnan *et al.*, 2024). While big data offers various techniques like clustering and classification, text mining is best suited for extracting insights from unstructured mobile app reviews.

Despite the growing number of studies utilizing text mining methods to analyse user reviews, no systematic literature review currently exists that synthesizes these methods specifically within the context of mobile banking. While several papers have highlighted the importance of text mining for extracting insights from user feedback, they often focus on specific methods or isolated case studies. This lack of synthesis creates a gap in the literature, as researchers and practitioners lack guidance on the most relevant and effective text mining methods to apply in mobile banking contexts. Addressing this gap, the present study aims to provide a thorough synthesis of text mining approaches used for analysing mobile banking application reviews, offering a valuable resource for future research and practical applications. In fact, this paper presents a systematic literature review used to study previous research that used text mining to evaluate M-Banking user satisfaction. A systematic search is conducted to identify relevant articles from four selected databases: Google Scholar, Scopus, IEEE Xplore, and ScienceDirect. This paper is organized as follows. The next section presents the methods used for the search strategy and selection criteria. Then follow the results and discussion. A further section presents the proposed framework and outlines future directions for text mining in M-Banking applications. Finally, the conclusion and suggestions for future research are presented in the last section of the paper.

Methods

Systematic search strategy

A systematic search was conducted to identify relevant articles from selected databases as of November 27, 2024, without applying any specific start-date restrictions. No start-date restriction was applied to capture the full evolution of text mining applications in M-Banking and ensure no relevant foundational work was excluded. The four databases utilized for this search were Google Scholar, Scopus, IEEE Xplore, and ScienceDirect, which together provide wide coverage (Singh, V., *et al.*, 2021).

The search terms were designed with a two-part structure to target titles explicitly addressing mobile banking applications and relevant text-mining methods. Search terms were developed in consultation with both an academic expert, who has several publications in scientific journals, and an M-Banking practitioner with more than five years' experience in the banking sector, while cross-referencing high-impact studies to ensure comprehensive coverage and relevance.

Mobile Banking Focus: The first part of the query targeted articles referencing mobile banking applications in their titles. Six terms were chosen to guarantee extensive coverage: "Mobile Banking", "M-Banking", "Banking App", "Banking Apps", "Banking Application" and "Banking Applications".

Text Mining Relevance: The second part aimed to capture methodologies and topics related to text mining. Twenty-nine terms were identified in order to express this scope: "Text", "Mining", "Topic modeling", "Sentiment", "Sentiments", "Semantic", "User-generated", "UGC", "Extract", "Extracts", "Extraction", "Extracting", "Content", "Contents", "Reaction", "Reactions", "Reviews", "Comment", "Comments", "Feedback", "Feedbacks", "Opinion", "Opinions", "Emotion", "Emotions", "Response", "Responses", "Insight" and "Insights".

The combined logical query was structured as follows:

("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Text OR Mining OR "Topic modeling" OR Sentiment OR Sentiments OR Semantic OR "User-generated" OR UGC OR Extract OR Extracts OR Extraction OR Extracting OR Content OR Contents OR Reaction OR Reactions OR Reviews OR Comment OR Comments OR Feedback OR Feedbacks OR Opinion OR Opinions OR Emotion OR Emotions OR Response OR Responses OR Insight OR Insights).

The process of selecting the articles and the inclusion and exclusion criteria are explained in the next section. To ensure transparency and reproducibility, a comprehensive description of the search strategy, including all keywords and database specific search configurations, is provided in Table A1 (Appendix).

Inclusion and exclusion criteria

Following the searches conducted in the previously specified databases and parameters, the results were exported to an Excel file, with the output of each database placed in a separate sheet. The search generated 187 results from Google Scholar, 68 from Scopus, 5 from IEEE Xplore, and 10 from ScienceDirect, resulting in a total of 270 identified articles. The first step involved consolidating all these entries into a single sheet, where duplicate records were removed, reducing the count by 109 to 161 unique articles.

Subsequently, 23 articles older than 10 years (using outdated methods) were excluded, leaving 138 articles for further screening. Of these, 21 articles were excluded for not being in English, narrowing the selection to 117 articles. An additional 5 articles were removed for being irretrievable or not meeting the criteria for scientific papers, leaving 112 articles. A preliminary assessment of titles and abstracts led to the exclusion of 61 articles deemed ineligible, resulting in 51 articles for full-text evaluation. Finally, after a detailed review, 11 articles were excluded for not meeting the eligibility criteria, based on a full-text assessment, which ensured that each study explicitly applied text-mining methods to M-Banking comments, leaving 40 usable articles for inclusion in the study. To minimize bias, two independent researchers reviewed the data and resolved disagreements through discussion. The systematic literature review procedure described above is illustrated in Figure 1.

Characteristics of included studies

Sources

The studies analysed in this paper utilized a variety of data sources to collect information on M-Banking apps. A significant portion of the studies relied solely on the Google Play Store, with 27 studies using it as their primary source. Some studies extended their data collection to include both the Google Play Store and the App Store, with 7 studies combining these two platforms. A few studies broadened their scope further by incorporating other sources, in addition to the Google Play Store and App Store, with 2 studies utilizing this combination. One study focused only on the Google Play Store and other sources, whereas another exclusively relied on the App Store. Additionally, one study utilized Twitter as its sole source for data collection. Figure 2 shows this distribution.

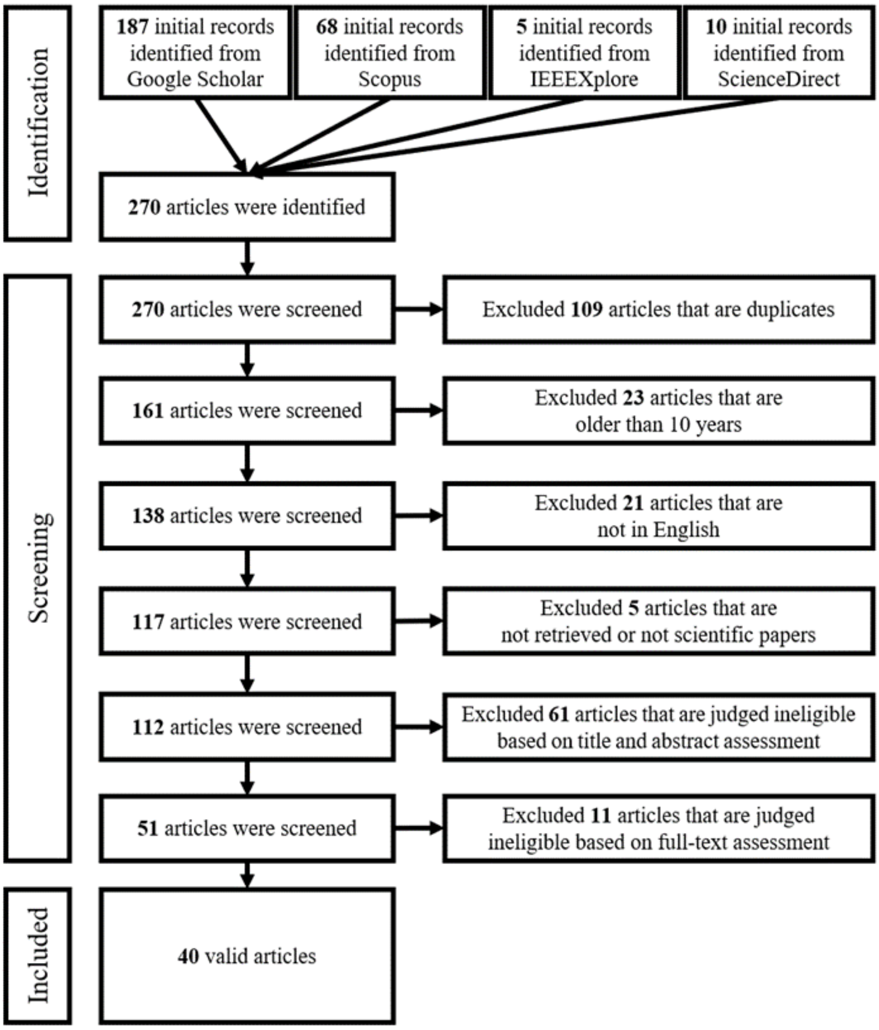

Figure 1. Process of selecting the articles

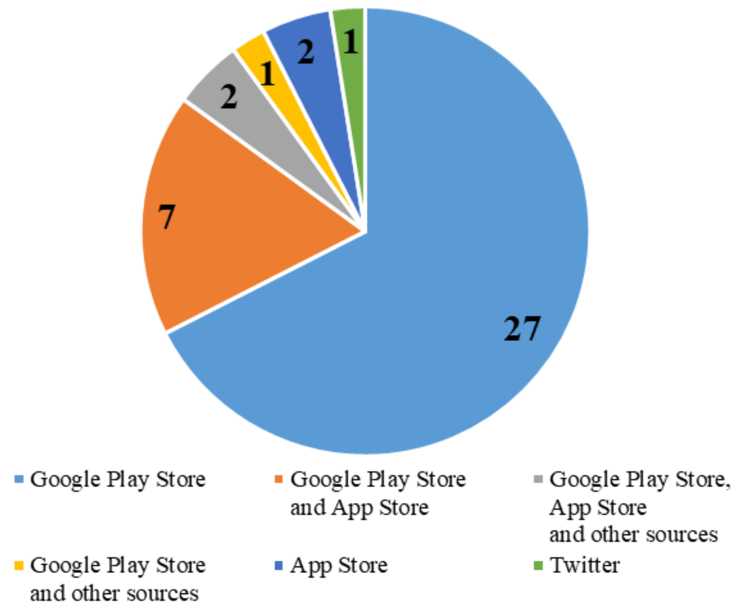

Figure 2. Data sources utilized in the studies

Number of studied M-Banking apps per paper

The distribution of studies based on the number of studied M-Banking apps reveals varying levels of focus. Most studies analyse a single M-Banking app, with 13 studies falling into this category. Fifteen studies examine between 1 and 10 apps, whereas 5 studies cover between 10 and 20 apps. Six studies investigated 20 or more apps, and one study did not specify the number of apps analysed. This distribution highlights the different scopes of research in the field, with a significant concentration on fewer apps in most studies. Figure 3 shows this distribution.

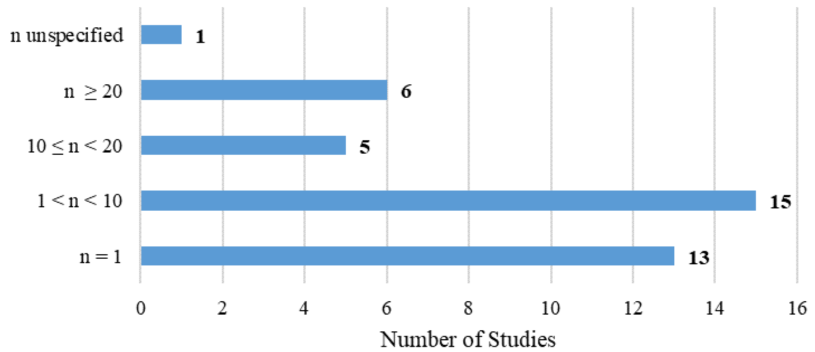

Figure 3. Distribution of the studied M-Banking apps per paper

Sample size

The sample sizes in the studies on M-Banking apps vary significantly, reflecting the scale of data collection across different research efforts. Eight studies analysed between 0 and 5,000 reviews, whereas 15 studies used sample sizes ranging from 5,001 to 20,000 reviews. A similar number of studies, 8, focused on a larger sample size of 20,001 to 100,000 reviews. Six studies analysed between 100,001 and 500,000 reviews, and one study investigated more than 500,000 reviews. Additionally, two studies did not specify the number of reviews used in their analysis. This range of sample sizes underscores the varying levels of data used in research within this field. Figure 4 shows this distribution.

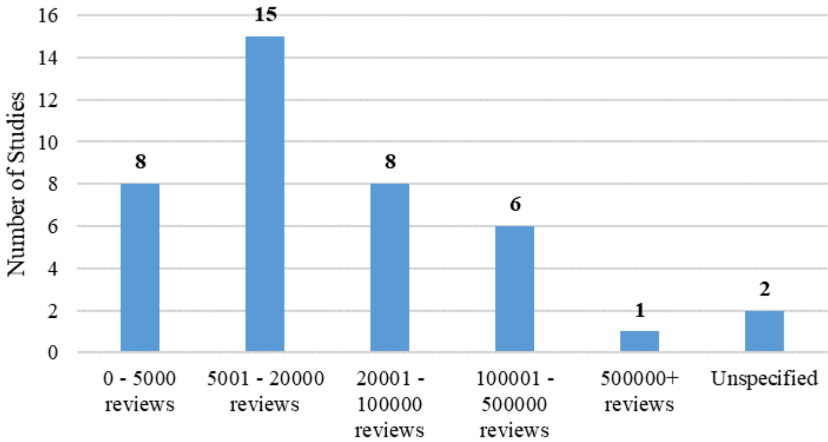

Figure 4. Sizes of the reviews analysed in the studies

Sample period

The clarity of the period specification across the studies analysed reveals a notable distribution. Most studies explicitly defined the sample period, accounting for 22 studies. A smaller number, 7, provided a partially specified sample period, whereas 11 studies did not define the sample period at all. Table 1 presents the distribution of studies based on the clarity of sample period specification.

The timeline graph in Figure 5 maps the explicitly defined periods, showing a concentration of studies between 2019 and 2024. This clustering suggests increased research activity in recent years, likely driven by advances in text mining and the global expansion of M-Banking.

Table 1. Definition of sample periods in the included studies

Period definition	Studies
Explicitly defined	Bahauddin *et al.* (2024) Adiningtyas & Auliani (2024) Bimantara & Zufria (2024) Edwina (2024) Basu *et al.* (2024) Kim & Ryu (2024) Okatan & Çam (2024) Dey *et al.* (2023) Alismail & Albesher (2023) Sari *et al.* (2023) Adiningtyas & Auliani (2023) Çallı (2023) Halvadia *et al.* (2022) Oh & Kim (2022) Shankar *et al.* (2022) Al-Hagree & Al-Gaphari (2022) Omotosho (2021) Tabiaa & Madani (2021) Asali (2021) Leem & Eum (2021) Leem (2021)

Period definition	Studies
	Permana *et al.* (2020)
Partially specified	Jamadar *et al.* (2024) Lubis (2024) Abd Rahman *et al.* (2022) Adebiyi & Omotosho (2022) Singh, G., *et al.* (2021) Amalia & Nafan (2021) Mohan *et al.* (2016)
Not defined	Balcıoğlu (2024) Desiraju *et al.* (2024) Alrizq & Alghamdi (2024) Berru *et al.* (2024) Mahmood *et al.* (2023) Sally (2023) Hussain *et al.* (2023) Khabour *et al.* (2023) Shinde (2022) Misinem *et al.* (2022) Dinçer *et al.* (2020)

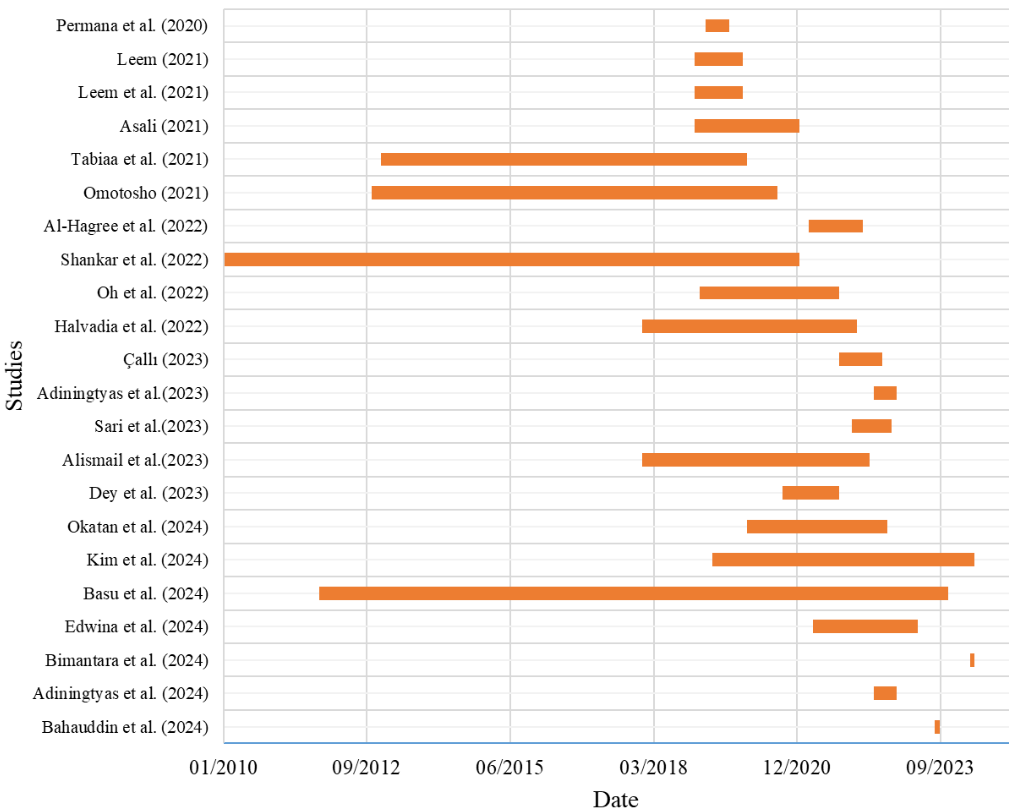

Figure 5. Timeline of sample periods in included studies

Mining techniques

A variety of techniques were employed for data mining across the studies reviewed. The most used was Python-based web scraping, which was utilized by 12 studies. Other notable techniques include WebHarvy, which was used by 4 studies, and Heedzy, which was employed by 2 studies. Several studies have applied unique or unspecified techniques, such as manual extraction combined with web scraping (one study), or various Python-based approaches, such as Jupyter Notebook and Python-based web crawlers. There were also cases where the technique was unspecified, accounting for 10 studies. Table 2 shows the distribution of techniques used for data mining in the studies.

Table 2. Techniques for text mining in the studies

Technique	Number of studies
Scraping (Python)	12
Scraping (Google Colab)	1
Scraping (Data Miner)	1
Scraping (without specification)	3
WebHarvy	4
Heedzy	2
A web scraper app and manual extraction	1
Web scraping	1
Github	1
Python and Jupiter Notebook	1
Python-based web crawler	1
Google Play Store public API	1
A script in JavaScript	1
Unspecified	10

Methods applied in reviews analysis

Figure 6 shows the distribution of methods applied in the studies. Notably, most of the papers use more than one method. Sentiment analysis is the most widely applied method, used in 28 papers (70%). Topic modelling followed with 17 papers (42.5%), and word cloud analysis was utilized in 16 papers (40%). Other methods were employed in 14 papers (35%).

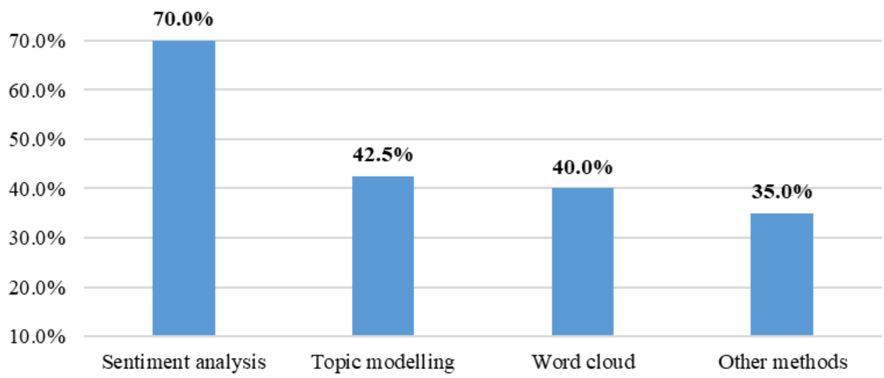

Figure 6. Methods applied in the studies

Results and Discussion

This section synthesizes the findings of this systematic literature review, addressing key trends, geographic distribution, data collection practices, and analytical techniques and methods employed in studies on M-Banking apps and text mining. This review highlights common themes and new trends, providing a clear understanding of the current research landscape and its importance for future studies and real-world uses.

Results

Table 3 presents a summary of studies on M-Banking apps and text mining, detailing the authors, data sources, countries, number of apps, sample sizes, and mining techniques such as scraping. It highlights the methods applied, such as sentiment analysis and topic modelling, to analyse user feedback and trends. Key findings from each study are included, offering insights into customer satisfaction, app issues, and recommendations for improvement. It is worth noting that the same author utilized an identical dataset for both studies presented in Leem (2021) and Leem & Eum (2021).

Table 3. Summary of studies on text mining and M-Banking apps

Study	Mining details	Applied methods	Key findings
Balcıoğlu (2024)	Source: Google Play Store Country: Turkey Number of studied apps: 10 Sample size: 139994 Period: - Mining technique: Scraping (Python: "google-play-scraper")	Sentiment analysis Trend analysis Topic modelling Word cloud	When software updates or service feature changes occur, negative reviews tend to outnumber good ones. The results emphasize how M-Banking apps must be continuously tested and improved to successfully satisfy user expectations.
Bahaud-din *et al.* (2024)	Source: Google Play Store Country: - Number of studied apps: 1 Sample size: 5566 Period: From August 2023 to September 2023 Mining technique: -	Sentiment analysis	Strategies to minimize unnecessary animation and the use of live wallpapers, optimize tools, application features, and memory utilization, develop an update system, offer content localization features, and consistently integrate user feedback into application enhancements are among the outcomes.
Adining-tyas & Auliani (2024)	Source: Google Play Store Country: Indonesia Number of studied apps: 3 Sample size: 6000 Period: From June 1, 2022, to November 5, 2022 Mining technique: -	Sentiment analysis	Poor service quality was offered by the M-Banking apps that were investigated. Privacy, system availability, efficiency, and compliance must all be considered considering the many unfavourable views. This work suggests that the three studied M-Banking apps need to improve their offerings in order to keep users.
Biman-tara & Zufria (2024)	Source: Google Play Store Country: Indonesia Number of studied apps: 1 Sample size: 1500 Period: April 2024 Mining technique: Scraping (Python in Google Colab)	Sentiment analysis Word cloud	The SVM algorithm is calculated using the TF-IDF and NLP technique, and training data is used to train the algorithm. According to the computation results, the model's accuracy is 92%. Approximately 92% is the precision score, 100% is the recall score, and 95% is the F1 score.
Jamadar *et al.* (2024)	Source: Google Play Store Country: India Number of studied apps: 6 Sample size: 3000 (the newest 500 English reviews were collected for each app) Period: Up to September 22, 2023 Mining technique: Scraping	Sentiment analysis Topic modelling Word cloud	The results showed that user experience is mainly determined by customer support service, features and functionality of apps, and app performance.

Study	**Mining details**	**Applied methods**	**Key findings**
Lubis (2024)	Source: Google Play Store Country: Indonesia Number of studied apps: 2 Sample size: 5670 Period: Comments within the last two years Mining technique: Scraping (Google Colab)	Sentiment analysis Descrip-tive analysis	The results suggest that a key factor in positive user sentiment is "trust in the application", including security and integrity as well as its pertinent features. The results emphasize how crucial it is to enhance application functionality and trust in order to boost customer loyalty and satisfaction.
Edwina *et al.* (2024)	Source: Google Play Store and App Store Country: Indonesia Number of studied apps: 1 Sample size: 7017 Period: From April 2021 to March 2023 Mining technique: Scraping (Python: "google_play_store" and "app_store_scraper")	Sentiment analysis Topic modelling	The findings reveal a number of recurrent themes in user feedback, including login/update errors, transaction failures, and requests for new features.
Basu *et al.* (2024)	Source: Google Play Store and App Store Country: India Number of studied apps: 2 Sample size: 347000 (157000 from Google Play Store and 190000 from App Store) Period: From November 2011 to October 2023 Mining technique: Scraping ("google_play_scraper" and "app_store_scraper")	Topic modelling	While technology-trusting expectations also affect the promoting intention for the second M-Banking app, perception of resources, Internet fear from cyberthreats, technology-trusting performance, all have a major impact on the first M-Banking apps promoting intention.
Desiraju *et al.* (2024)	Source: Google Play Store Country: The United States Number of studied apps: 9 Sample size: 89788 Period: - Mining technique: Python-based web crawler	Topic modelling Structural topic modelling Word cloud	The study emphasizes that, while account navigation and personalized user experience have a negative effect on satisfaction, customer service, ease of user interaction, and digital assistance have a favourable effect.
Kim & Ryu (2024)	Source: Google Play Store Country: Korea Number of studied apps: 3 Sample size: 106362 Period: From May 1, 2019, to April 30, 2024 Mining technique: Scraping (Python: "selenium", "beautifulsoup" and "google-play-scraper")	Sentiment analysis Topic modelling Keyword analysis	The results of the case study show that Korean M-Banking apps are becoming more and more aesthetically pleasing, but they also underscore the urgent need for improvements in crucial areas like security and stability, which are especially relevant to the financial sector.
Alrizq & Algham-di (2024)	Source: Google Play Store Country: Saudi Arabia Number of studied apps: 2 Sample size: 4149 Period: - Mining technique: -	Topic modelling	The results showed that a customer's level of satisfaction with online banking apps may be effectively confirmed by utilizing the criteria identified by text mining and predictive machine learning.

Study	Mining details	Applied methods	Key findings
Berru *et al.* (2024)	Source: Google Play Store, App Store and responses were collected from a survey developed through Google Forms Country: - Number of studied apps: 1 Sample size: - Period: - Mining technique: Scraping	Sentiment analysis Word cloud	Data security and availability are the primary issues while utilizing M-Banking, and user satisfaction, security and privacy concerns, app usability, and customer service quality are found to be diverse.
Okatan & Çam (2024)	Source: Many Social Sharing Forum Sites and Google Play Store Country: Turkey Number of studied apps: 13 Sample size: 1200000-1250000 Period: From January 2020 to August 2022 Mining technique: Python and Jupiter Notebook	Sentiment analysis Word cloud	Customers of banks most commonly mention “the ease”, “usefulness” and “service fees of digital applications”.
Dey *et al.* (2023)	Source: Google Play Store Country: Bangladesh Number of studied apps: 1 Sample size: Over 10000 Period: From September 2020 to September 2021 Mining technique: WebHarvy	Sentiment analysis Topic modelling Word cloud	By identifying and preventing service outages early on, customer satisfaction levels can rise. Positive comments include “nice”, “thanks”, “convenience”, “good”, and “easy”. The terms “inconvenience” and “problem” are used in certain remarks by people who are having trouble with their utility bills and passwords. Performance, email, fund transfers, account management, passwords, utility, accounts, service, and delivery of service are the nine main subjects that topic modelling revealed covered the reviews that were recorded.
Abd Rahman *et al.* (2023)	Source: Google Play Store Country: Malaysia Number of studied apps: 6 Sample size: 50170 Period: On 7th March 2020 focusing on first 100 pages in user review section Mining technique: WebHarvy	Sentiment analysis Word cloud	When an application is up to date, easy to use, and capable of resolving issues during transactions, the user is satisfied. The performance of the application in completing the online transaction is directly linked to the negative sentiments.

Study	**Mining details**	**Applied methods**	**Key findings**
Alismail & Albesher (2023)	Source: Google Play Store and App Store Countries: Saudi Arabia and the United States Number of studied apps: 20 (10+10) Sample size: The United States: 84085 (81874 from Google Play Store and 2211 from the App Store) and Saudi Arabia: 3089 (2287 from Google Play Store and 802 from the App Store) Period: From January 2018 to April 2022 Mining technique: Python	Content analysis Qualitative analysis Quantitat-ive analysis	Three categories of responses were identified by the study in the answers of developers: interactive, semi-interactive, and no reaction. One key finding is that both in terms of quantity and quality of responses, the United States bank app developers performed better than Saudi bank app developers.
Mah-mood *et al.* (2023)	Source: Google Play Store Country: Pakistan Number of studied apps: 10 Sample size: 142673 Period: - Mining technique: Scraper ("google_play_scraper")	Sentiment analysis Thematic analysis Word cloud	The thematic analysis reveals 441 negative themes, including poor app updates or new versions, account registration issues, app crash issues, and performance issues, while 346 positive themes are found, including "ease of use", "helpful", "reliable", "user-friendly", "good aesthetics", "convenience", "secured", and many more.
Sari *et al.* (2023)	Source: Google Play Store Country: Indonesia Number of studied apps: 4 Sample size: 72027 Period: From January 2022 to September 2022 Mining technique: Web scraping	Sentiment analysis	Based on the findings of review evaluations, this study recommends that banks should enhance the performance and system of the M-Banking app to better meet the needs of their customers.
Adining-tyas & Auliani (2023)	Source: Google Play Store Country: Indonesia Number of studied apps: 1 Sample size: 2000 Period: From June 1, 2022, to November 5, 2022 Mining technique: Scraping	Sentiment analysis Topic modelling	Users are not happy with the app's service. Because the most recent version of the mobile app does not use pins or one-time passwords (OTP), users view transactions with it as dangerous. This finding might enable the bank to focus more on other app features to better understand their clients' wants.
Calli (2023)	Source: Google Play Store Country: Turkey Number of studied apps: 2 Sample size: 21526 Period: From January through July 2022 and the fourth quarter of 2021 Mining technique: Scraping (Python)	Topic modelling	By considering user reviews based on their experiences, 11 topics were identified. When evaluating M-Banking apps, "perceived usefulness", "convenience", and "time-saving" are accorded far higher weight than other factors. Additionally, seven themes relating to technical and security issues with M-Banking apps have been identified.
Sally (2023)	Source: Google Play Store Country: Sri Lanka Number of studied apps: 10 Sample size: 20296 Period: - Mining technique: Scraping (Python: "google-play-scraper")	Sentiment analysis Topic modelling	The findings showed that the main reasons for consumer discontent are unstable versions following recent updates, poor customer support, and incorrect functional and nonfunctional features.

Study	Mining details	Applied methods	Key findings
Hussain *et al.* (2023)	Source: Google Play Store Country: Pakistan Number of studied apps: 24 Sample size: 76168 Period: - Mining technique: Scraping (Python: "google-play-scraper")	Topic modelling	While unfavourable reviews talk about "system availability", "responsiveness", "faulty updates", "login issues", and "reliability", positive evaluations emphasize "security", "convenience", "ease of use", "continuous improvement", "usefulness", and "app attributes".
Khabour *et al.* (2023)	Source: Businesses websites and mobile applications Country: Jordan Number of studied apps: 1 Sample size: 9819 Period: - Mining technique: A web scraper app and manual extraction	Sentiment analysis Emotion mining Word cloud	Banks will be able to learn how to improve their online presence and satisfy stakeholders and consumers' needs thanks to the suggested methodology.
Shinde (2022)	Source: Google Play Store Country: India Number of studied apps: 1 Sample size: - Period: - Mining technique: -	Sentiment analysis	Customers will be able to choose the most popular application with the assistance of the reviews, which will assist the developers in keeping their applications updated and in the top lists.
Adebiyi & Omo-tosho (2022)	Source: Google Play Store and App Store Country: Nigeria Number of studied apps: 24 Sample size: 158047 Period: From as of April 25, 2022 Mining technique: Heedzy	Sentiment analysis Word cloud	The most common emotion in the corpus was "trust", which was followed by "anticipation", "joy", and "surprise"; "disgust" was the feeling category with the lowest frequency. The study suggests that banks focus more on user reviews on their M-Banking apps to address legacy issues that are causing their customers to consistently express negative sentiments and low ratings. To stay competitive and maintain their clients' trust, banks with regional authorization are urged to make investments in their IT infrastructure.
Halvadia *et al.* (2022)	Source: Google Play Store Country: India Number of studied apps: 3 Sample size: 5294 Period: From January 2018 to January 2022 Mining technique: -	N-gram analysis Word cloud	Users of Indian public sector banks M-Banking apps are happy and satisfied since they believe the app is "secure", "convenient", and "easy to use". Public sector banks in India ought to market their M-Banking apps as secure and easy for money transfers. Managers of Indian public sector banks can use the research's conclusions to increase customer loyalty, attract new clients, and effectively market their M-Banking apps.
Oh & Kim (2022)	Source: Google Play Store and App Store Country: The United States Number of studied apps: 4 Sample size: 96140 Period: From February 2019 to October 2021 Mining technique: -	Topic modelling	According to the research findings, the most important element influencing consumer satisfaction with mobile financial services is "security".

Study	**Mining details**	**Applied methods**	**Key findings**
Shankar *et al.* (2022)	Source: Google Play Store and App Store Country: - Number of studied apps: 8 Sample size: 6073 Period: Between 2010 and 2020 Mining technique: -	Latent Semantic Analysis (LSA)	The findings showed that the most important elements are "privacy and security", "navigation", "customer support", "convenience" and "efficiency".
Al-Hagree & Al-Gaphari (2022)	Source: Google Play Store Country: Yemen Number of studied apps: 8 Sample size: 3545 Period: From March 5, 2021, to March 16, 2022 Mining technique: Github (https://github.com/salahalhagree/Banking_services_mobile_apps)	Sentiment analysis	The reviews compiled in this study are in Arabic, and as many reviewers use nonstandard language, it can be difficult to understand what some of the words represent.
Misinem *et al.* (2022)	Source: Google Play Store Country: Malaysia Number of studied apps: 1 Sample size: 7454 Period: - Mining technique: Scraping (Data Miner is one of the data scrapper extensions installed in Google Chrome)	Sentiment analysis Word cloud	Five algorithms (Linear Regression, Naïve Bayes, Decision Tree, Random Forest, and Support Vector Machine) were used to compare the dataset. The Decision Tree algorithm produced the best accuracy result (94.37%), while Naïve Bayes produced the least (66%).
Omo-tosho (2021)	Source: Google Play Store and App Store Country: Nigeria Number of studied apps: 22 Sample size: 37460 Period: From November 2012 to July 2020 Mining technique: Heedzy	Sentiment analysis Topic modelling Word cloud	"Trust", "anticipation", and "joy" account for 66% of the emotions that users express, while "surprise", "fear", "anger", and "disgust" account for 34%. Primary topics are: (1) feedback on banks' responsiveness to user complaints; (2) user experience regarding app functionalities and updates; and (3) operational failures associated with the use of the apps. These findings demonstrate the necessity for banks to keep raising user knowledge of the features already available on their apps, instructing users on how to access such solutions, and rapidly and effectively responding to user feedback.
Tabiaa & Madani (2021)	Source: Google Play Store Country: Morocco Number of studied apps: 8 Sample size: 48493 Period: From January 2013 to December 2019 Mining technique: A script in JavaScript that allows scraping and downloading all comment	Topic modelling Word cloud	The topics found mostly focused on "security", "services", "quality", and "interface".

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Study	Mining details	Applied methods	Key findings
Singh, G., *et al.* (2021)	Source: App Store Country: India Number of studied apps: 10 Sample size: 9516 Period: Pre-COVID (2018-2019) and during COVID (2020–2021) Mining technique: Python	Sentiment analysis	It has been recommended that financial institutions monitor the shifting attitudes of their customers, as this can serve as a solid foundation for improved strategy development and customer retention.
Asali (2021)	Source: Twitter Country: Indonesia Number of studied apps: - Sample size: 5014 Period: From January 1, 2019, to December 31, 2020 Mining technique: Tweets include the words “mobile banking”, “m-banking”, or “mbanking” plus one of the nine features (payment, block, open new bank account, login, transaction report, bank balance, top-up, transaction, and transfer)	Sentiment analysis	Some suggestions for banks to enhance the performance of their M-Banking apps include: ensuring that there are no additional fees for accessing any feature; offering a record or follow-up that can be recalled following each significant action or transaction; ensuring that the M-Banking app remains responsive to customer needs while maintaining it “steady”, “fast”, and “easy to use” and improving synchronization, particularly when dealing with third-party entities like other banks and e-money and digital wallet service providers.
Leem & Eum (2021)	Source: Google Play Store Country: Korea Number of studied apps: 1 Sample size: 3900 Period: From January 1, 2019, to December 31, 2019 Mining technique: WebHarvy	Sentiment analysis Keyword analysis	Finding client complaints on a regular basis helps to increase customer satisfaction and service quality while also preventing service breakdowns early.
Amalia & Nafan (2021)	Source: Google Play Store Country: Indonesia Number of studied apps: 1 Sample size: 1200 Period: The latest rows submit on October 9, 2021 Mining technique: -	Classific-ation (Multi-nomial Naïve Bayes algorithm)	Multinomial Naïve Bayes performed a good result of classification proved by accuracy score (0.822) and weighted average score of precision (0.83), recall (0.94) and F1 (0.99).
Leem (2021)	Source: Google Play Store Country: Korea Number of studied apps: 1 Sample size: 3900 Period: From January 1, 2019, to December 31, 2019 Mining technique: WebHarvy	Sentiment analysis Topic modelling	According to this study, the most common service complaints were “unhelpfulness of customer service staff” (11%), “app installation error” (26%), “recognition error” (17%), “connection failure” (16%), “error after update” (16%), and “authentication failure” (15%).

Study	Mining details	Applied methods	Key findings
Dinçer *et al.* (2020)	Source: App Store Country: Turkey Number of studied apps: 24 Sample size: 12000 (last 500 customer comments of each bank) Period: - Mining technique: -	IT2 fuzzy DEMATEL method-ology	According to the results, the most crucial factors influencing user satisfaction with mobile apps are "usability" and "operational" dimensions. Customers place a high value on the quality and variety of services provided by mobile applications. Therefore, it is advised that banks offer a variety of services in these apps, including money transfers and credit card payments. It is also critical that these apps be well-designed to enable the user to perform their tasks with ease.
Permana *et al.* (2020)	Source: Google Play Store Country: Indonesia Number of studied apps: 1 Sample size: 6194 Period: From March 16, 2019, to August 27, 2019 Mining technique: Scraping ("google_play_scraper")	Sentiment analysis Topic modelling	The most common subjects covered in negative classes are "network connections", "application login issues", and "limitations on OTP code delivery". However, "ease", "simplicity", and "helpfulness" were the most often discussed topics in positives classes.
Mohan *et al.* (2016)	Source: Google Play Store Country: India Number of studied apps: 51 Sample size: 303694 Period: Since January 2015 Mining technique: Google Play Store public API	Sentiment analysis Word cloud	Based on several usability criteria, the study recommends the Mobile App Usability Index (MAUI) as a metric for enhancing usability. Sentiment analysis was used to formulate the parameters.

Trends in publication over time

Figure 7 illustrates the annual distribution of research papers on M-Banking apps and text mining from 2014 to 2024 (the period already used in the selection process). Results reveal an increase in the number of papers published over the years.

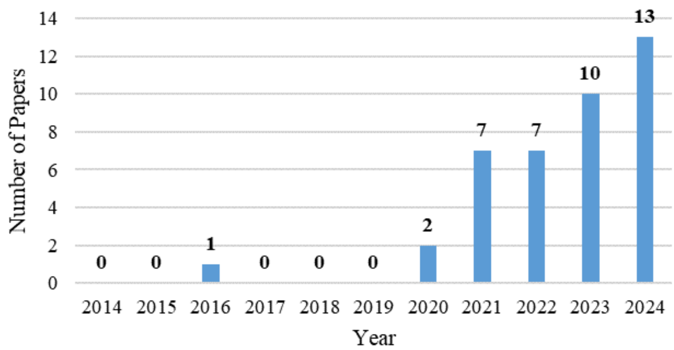

Figure 7. Time analysis of papers by year: 2014–2024

Starting with no papers published in 2014, 2015, 2017, or 2018, the first paper was published in 2016. After that, the number of papers rises slightly in 2020, with two papers, followed by a more significant increase from 2021 onward, with seven papers published in both 2021 and 2022. The growth continues in 2023, with ten papers, and in 2024, thirteen papers were published. This pattern underscores the growing academic interest in M-Banking and text mining, especially from 2021 onward. This growth is due to more people using M-Banking

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worldwide, improvements in text mining and big data tools, and the increasing amount of user-generated data.

Geographic distribution of research

The geographic distribution of the 40 usable papers on M-Banking apps and text mining reveals a varied global interest, with some countries contributing more significantly to the field than others do. As shown in Figure 8, Indonesia has the highest number of papers, with nine. India follows with six papers, whereas Turkey contributes four. Other countries, such as Korea, Malaysia, and Pakistan, have published two papers each. The United States, with two papers, alongside countries such as Sri Lanka, Jordan, Yemen, Morocco, and Bangladesh, each contributing one paper, shows more limited involvement. Notably, there is also a combined entry for “Saudi Arabia and the United States”, which accounts for three papers for the United States, indicating potential collaborative or overlapping research efforts.

Additionally, the category labelled “unspecified” includes three papers, representing research that did not explicitly mention a geographic focus. This distribution highlights the areas where academic interest in M-Banking and text mining is most concentrated, with a notable concentration in Southeast Asia, South Asia, and the Middle East. Countries like Indonesia and India may dominate the publication count due to factors such as rapid fintech adoption, supportive government initiatives in digital banking, and an active research community in digital fields.

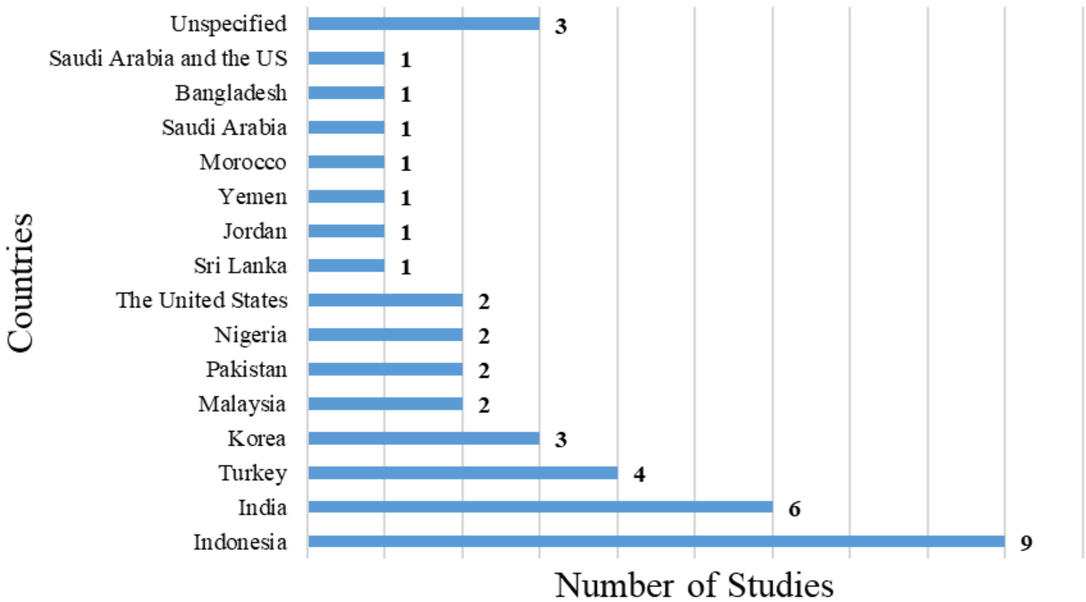

Figure 8. Geographic distribution of M-Banking apps and text mining studies

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Data availability in selected studies

Figure 9 shows the availability of mining details in the selected studies. These include sources, covered countries, the number of studied apps, sample sizes, study periods, and the mining techniques used. This helps identify what information is available and what is missing.

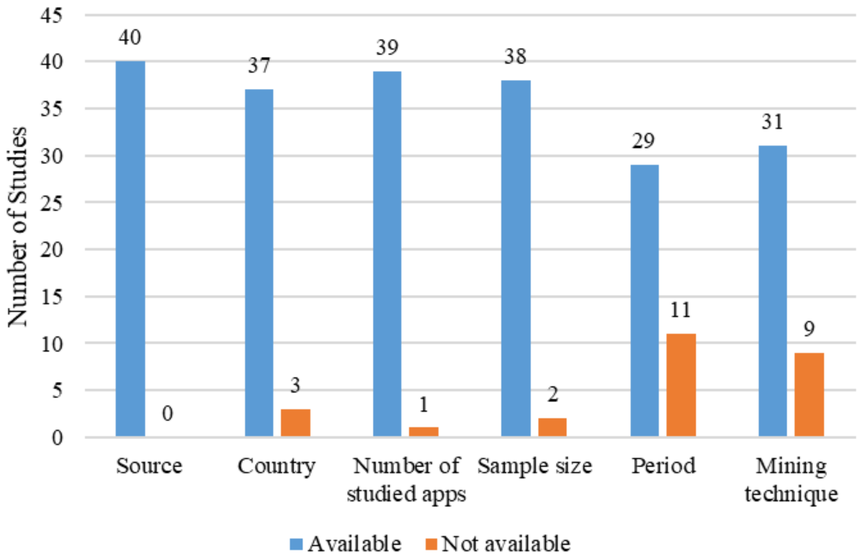

Figure 9. Availability of mining parameters

Thematic analysis

Numerous themes related to customer satisfaction and dissatisfaction are revealed by the examination of M-Banking apps. For example, software updates (Balcıoğlu, 2024), unsuccessful transactions (Edwina, 2024), and inadequate customer service (Leem, 2021) are frequently associated with negative evaluations, underscoring the necessity of ongoing testing and development. Optimizing tools, resolving security issues, and integrating user input into software updates are some ways to improve the user experience. System availability (Hussain *et al.*, 2023; Berru *et al.*, 2024; Adiningtyas & Auliani, 2024), privacy issues (Berru *et al.*, 2024; Adiningtyas & Auliani, 2024), and app performance (Sari *et al.*, 2023; Mahmood *et al.*, 2023; Abd Rahman *et al.*, 2022) are frequently noted problems. The findings also demonstrate how user experience elements such as usability (Dinçer *et al.*, 2020; Berru *et al.*, 2024), trust (Omotosho, 2021; Adebiyi & Omotosho, 2022; Lubis, 2024), and ease of use (Desiraju *et al.*, 2024) affect satisfaction. Table 4 summarizes the popular themes mentioned in the studies.

Table 4: Popular themes in the studies

Theme	Sub-theme	Number of studies	Studies
Security and confidentiality	Security	10	Basu *et al.* (2024) Kim & Ryu (2024) Berru *et al.* (2024) Mahmood *et al.* (2023) Çallı (2023) Hussain *et al.* (2023)

Theme	Sub-theme	Number of studies	Studies
			Halvadia *et al.* (2022) Oh & Kim (2022) Shankar *et al.* (2022) Tabiaa & Madani (2021)
	Trust	4	Lubis (2024) Basu *et al.* (2024) Adebiyi & Omotosho (2022) Omotosho (2021)
	Privacy	2	Adiningtyas & Auliani (2024) Shankar *et al.* (2022)
Usability	Ease of use	9	Desiraju *et al.* (2024) Okatan & Çam (2024) Mahmood *et al.* (2023) Hussain *et al.* (2023) Halvadia *et al.* (2022) Abd Rahman *et al.* (2022) Asali (2021) Dinçer *et al.* (2020) Permana *et al.* (2020)
	Convenience	5	Mahmood *et al.* (2023) Çallı (2023) Hussain *et al.* (2023) Halvadia *et al.* (2022) Shankar *et al.* (2022)
	Login issues	5	Edwina (2024) Dey *et al.* (2023) Hussain *et al.* (2023) Leem (2021) Permana *et al.* (2020)
	Well-designed	3	Bahauddin *et al.* (2024) Mahmood *et al.* (2023) Dinçer *et al.* (2020)
Enhancements	Software updates	8	Balcıoğlu (2024) Edwina (2024) Mahmood *et al.* (2023) Sally (2023) Hussain *et al.* (2023) Abd Rahman *et al.* (2022) Leem (2021) Omotosho (2021)
	Continuous improvement	2	Balcıoğlu (2024) Hussain *et al.* (2023)
Technical quality of the system	Operational failures	7	Edwina (2024) Dey *et al.* (2023) Mahmood *et al.* (2023) Sally (2023) Omotosho (2021) Leem (2021) Dinçer *et al.* (2020)
	Performance	7	Jamadar *et al.* (2024) Basu *et al.* (2024) Dey *et al.* (2023) Mahmood *et al.* (2023) Sari *et al.* (2023) Abd Rahman *et al.* (2022) Asali (2021)

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Theme	Sub-theme	Number of studies	Studies
	Reliability	2	Mahmood *et al.* (2023) Hussain *et al.* (2023)
	Stability	2	Kim & Ryu (2024) Asali (2021)
Functional quality	Features / Functionality	6	Bahauddin *et al.* (2024) Jamadar *et al.* (2024) Lubis (2024) Edwina (2024) Hussain *et al.* (2023) Omotosho (2021)
	Usefulness	3	Okatan & Çam (2024) Çallı (2023) Hussain *et al.* (2023)
	Efficiency	2	Adiningtyas & Auliani (2024) Shankar *et al.* (2022)
	Helpfulness	2	Mahmood *et al.* (2023) Permana *et al.* (2020)
Customer service quality	Customer support	6	Jamadar *et al.* (2024) Desiraju *et al.* (2024) Sally (2023) Shankar *et al.* (2022) Leem (2021) Omotosho (2021)
	Service	4	Dey *et al.* (2023) Adiningtyas & Auliani (2023) Tabiaa & Madani (2021) Dinçer *et al.* (2020)
	Responsiveness	2	Hussain *et al.* (2023) Asali (2021)
Availability and accessibility	Availability	3	Adiningtyas & Auliani (2024) Berru *et al.* (2024) Hussain *et al.* (2023)
	Connection failure	2	Leem (2021) Permana *et al.* (2020)
Economic value	Service fees	2	Okatan & Çam (2024) Asali (2021)

Framework and Future Directions for Text Mining in M-Banking Applications

As illustrated in Figure 10, text mining applied to M-Banking apps has emerged as a growing area of academic interest, particularly since 2021. This rise in research is linked to the COVID-19 pandemic, which increased reliance on digital services, particularly M-Banking. This systematic literature review proposes a comprehensive framework that identifies the key features examined in prior research, including countries, methodologies, mining techniques, databases, and drivers of user satisfaction. Additionally, in Figure 10, the framework outlines future research avenues for exploring critical themes related to text mining in the context of mobile applications. For instance, it is recommended to extend future studies to underexplored yet significant markets, such as China, to gain insights into user interactions with M-Banking apps in this context, where no prior studies currently exist. Regarding methodologies, commonly employed techniques such as sentiment analysis, topic modelling, and word cloud generation are suggested, as they have proven effective in prior research (Chebil *et al*., 2024). To ensure the reliability and validity of findings, this review advocates for the use of trusted data sources, such as the Google Play Store and the Apple App Store, and recommends analysing a substantial dataset—ideally comprising at least 5000 user reviews—to yield meaningful and robust results.

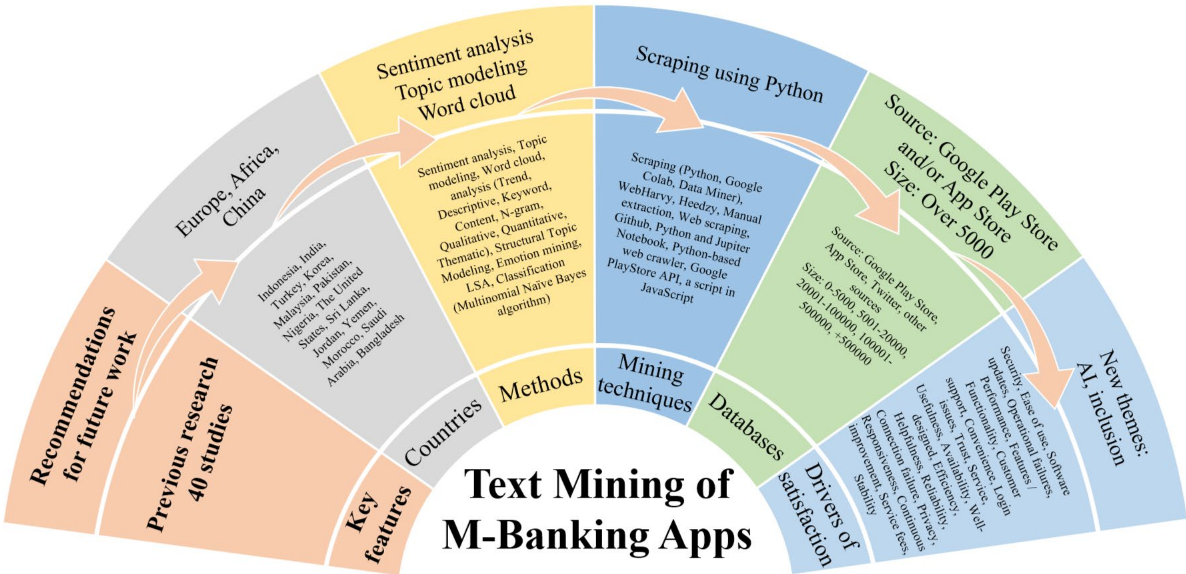

Figure 10. Framework and key insights for future research in text mining of M-Banking applications

For data collection, Python-based scraping tools are recommended due to their efficiency and widespread adoption in handling large datasets. Finally, the proposed framework emphasizes the importance of exploring new and critical themes in the context of text mining for M-Banking apps, such as enhancing security, implementing updates, and leveraging artificial intelligence or inclusivity to improve the overall user experience (Hentati & Jallouli, 2025a; 2025b).

To put these findings into practice, we suggest M-Banking developers focus on three key areas: regularly testing security updates with real users; using AI tools to monitor customer feedback; and creating dedicated teams to ensure app improvements meet user expectations. These practical steps, based directly on our reviews results, can help banks turn research insights into real-world solutions.

Future systematic reviews could benefit from incorporating AI-assisted screening tools such as Connected Papers and SciSpace. These platforms can enhance study identification while tracking emerging methodological trends, particularly the growing application of AI techniques in M-Banking research. Such tools would complement traditional review methods, offering more comprehensive coverage of this evolving field.

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Conclusion

This paper offers an informative analysis of research on text mining and M-Banking apps, highlighting significant trends and patterns over the past decade. The examination of the publication years of the studies shows a significant rise in attention, especially since 2021, which demonstrates the growing recognition of the importance of M-Banking apps in the digital economy. The regional distribution of the study indicates that the Middle East, South Asia, and Southeast Asia have all made substantial contributions.

Identifying trends in customer satisfaction has been made possible by the methods employed in these studies, such as sentiment analysis and topic modelling, of which sentiment analysis is the most popular. These methods provide valuable insights into the factors that determine the user experience, including security concerns, app updates, and customer service. This work also demonstrates a diverse range of research, with some studies expanding to evaluate large review datasets, whereas a significant portion focuses on a narrower selection of M-Banking apps.

In terms of practical applications, this review's conclusions can help M-Banking developers enhance their user experience by addressing frequent problems, including customer service, privacy concerns, and system availability. Gaining more consumer satisfaction and building trust in M-Banking apps require an understanding of these characteristics.

Furthermore, this paper contributes to academic literature by providing a comprehensive overview of the existing studies, offering valuable insights for future studies. Future research could: (1) conduct comparative analyses across different cultural and regulatory environments to better understand how user satisfaction with M-Banking vary globally; (2) explore advanced text mining techniques, such as deep learning-based sentiment analysis, to complement the methods identified in this review; (3) explore the integration of emerging technologies, such as artificial intelligence and robotics, into M-Banking apps; (4) combine the findings of this paper with practitioner perspectives and case studies to enhance generalizability; (5) extend the database coverage by incorporating additional scholarly repositories, such as SpringerLink, to ensure broader, more multidisciplinary inclusion; (6) prioritize including studies from Western contexts and emerging markets to provide a more balanced and comprehensive analysis; and (7) include non-English studies to capture wider international perspectives.

These directions could significantly contribute to improving both the functionality and security of M-Banking apps, as trust and security remain paramount user concerns, and recent regulatory developments, particularly increased liability of banking institutions to compensate fraud victims, have demonstrated that understanding user perspectives on security can

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directly inform both policy frameworks and technical implementations that enhance customer protection.

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Appendix

Table A1. Search strategies and query execution across databases

Databases	Search Process
Google Scholar	For Google Scholar, we conducted a systematic manual search to identify relevant literature. The search process involved generating combinations of keywords from two query segments and performing six distinct searches using the advanced search functionality. For each search, we applied the filter "where my words occur" set to "in the title of the article." The details of the searches are as follows: 1st search: "with the exact phrase": Mobile Banking "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights. 2nd search: "with the exact phrase": M-Banking "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights. 3rd search: "with the exact phrase": Banking App "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights. 4th search: "with the exact phrase": Banking Apps "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights. 5th search: "with the exact phrase": Banking Application "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights. 6th search: "with the exact phrase": Banking Applications "with at least one of the words": Text Mining "Topic modeling" Sentiment Sentiments Semantic "User-generated" UGC Extract Extracts Extraction Extracting Content Contents Reaction Reactions Reviews Comment Comments Feedback Feedbacks Opinion Opinions Emotion Emotions Response Responses Insight Insights
Scopus	For Scopus, a single search query was sufficient to retrieve the desired results due to the platforms less restrictive search parameters compared to other databases. The search query used was as follows: TITLE(("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Text OR Mining OR "Topic modeling" OR Sentiment OR Sentiments OR Semantic OR "User-generated" OR UGC OR Extract OR Extracts OR Extraction OR Extracting OR Content OR Contents OR Reaction OR Reactions OR Reviews OR Comment OR Comments OR Feedback OR Feedbacks OR Opinion OR Opinions OR Emotion OR Emotions OR Response OR Responses OR Insight OR Insights))

Databases	Search Process
Science-Direct	For ScienceDirect, it imposes a limit of 10 search terms per search clause. To accommodate this restriction and achieve comprehensive results, we executed fifteen separate search queries. The details of these queries are as follows: 1st command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Text OR Mining). 2nd command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND ("Topic modeling"). 3rd command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Sentiment OR Sentiments). 4th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Semantic OR Extraction). 5th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND ("User-generated" OR UGC). 6th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Extract OR Extracts). 7th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Extracting OR Content). 8th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Contents OR Reviews). 9th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Reaction OR Reactions). 10th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Comment OR Comments). 11th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Feedback OR Feedbacks). 12th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Opinion OR Opinions). 13th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Emotion OR Emotions). 14th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Response OR Responses). 15th command: ("Mobile Banking" OR "M-Banking" OR "Banking App" OR "Banking Apps" OR "Banking Application" OR "Banking Applications") AND (Insight OR Insights)

Databases	Search Process
IEEE Xplore	For IEEE Xplore, it allows a maximum of 25 search terms per search clause. To meet this limitation, we executed two separate search queries. The details of these queries are as follows: 1st command: ("Document Title":"Mobile Banking" OR "Document Title":"M-Banking" OR "Document Title":"Banking App" OR "Document Title":"Banking Apps" OR "Document Title":"Banking Application" OR "Document Title":"Banking Applications") AND ("Document Title":"Text" OR "Document Title":"Mining" OR "Document Title":"Topic modeling" OR "Document Title":"Sentiment" OR "Document Title":"Sentiments" OR "Document Title":"Semantic" OR "Document Title":"User-generated" OR "Document Title":"UGC" OR "Document Title":"Extract" OR "Document Title":"Extracts" OR "Document Title":"Extraction" OR "Document Title":"Extracting" OR "Document Title": "Content" OR "Document Title":"Contents" OR "Document Title":"Reaction" OR "Document Title":"Reactions" OR "Document Title": "Reviews" OR "Document Title":"Comment"). 2nd command: ("Document Title":"Mobile Banking" OR "Document Title":"M-Banking" OR "Document Title":"Banking App" OR "Document Title":"Banking Apps" OR "Document Title":"Banking Application" OR "Document Title":"Banking Applications") AND ("Document Title":"Comments" OR "Document Title":"Feedback" OR "Document Title":"Feedbacks" OR "Document Title": "Opinion" OR "Document Title":"Opinions" OR "Document Title": "Emotion" OR "Document Title": "Emotions" OR "Document Title": "Response" OR "Document Title": "Responses" OR "Document Title": "Insight" OR "Document Title":"Insights")

Australia's Broadband Evolution to 2007

Simon Moorhead
Telecommunications Manager

Abstract: The *Journal* revisits an historic paper, written by Peter Darling in 2007, which details Australia's evolving broadband policy as background to the decisions likely to be made by the incoming new Australian Government in that year. Broadband policy was a critical differentiator between the outgoing Coalition government and the incoming Labor government in the 2007 federal election. The paper is written for a broad readership within the Australian telecommunications industry.

Keywords: History of Australian Telecommunications, Broadband Evolution and Policy, *Telecommunication Journal of Australia*.

Introduction

Peter Darling (1946–2013) was a nationally recognized expert on new public telecommunication networks (Gerrand, 2013). It is notable that he was as highly regarded during the 1990s and 2000s by consumer groups (e.g., ACCAN) and business groups (e.g., ATUG) as he was by his employers in Telstra's network strategy and regulatory groups, for both his integrity and his technical expertise. He was also highly respected across the industry for the number of excellent tutorial papers he wrote for this journal's predecessor, the *Telecommunication Journal of Australia*, and this journal on a wide range of new network technologies and developments.

The revisiting of this historic paper (Darling, 2007) is timely, given the contested implementation of broadband policy in Australia since that time. The design of the National Broadband Network became the defining issue in resolving the 2010 federal election (Gerrand, 2010) and an ongoing source of policy differentiation between Australia's major parties in federal government until at least 2022.

Darling's paper describes the political consensus in the 1990s on the need to provide infrastructure competition to the former incumbent carrier, Telecom Australia (evolving into

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Telstra by 1991), while diverging on the need for privatization of Telstra. The paper reflects on the policy debate during the election campaign period – when the paper was written.

The paper provides an overview of the network technologies that were candidates for delivering broadband services in 2007 — most of which are still used in the Australian public network. This overview is followed by a comparison of the two major competing industry proposals to the federal government. The first was the Telstra 2005 proposal, using optical fibre to the premises (FTTP) in greenfield areas, and ADSL2+ over existing copper access networks — and the reasons given by the government for rejecting this. The second was the G9 proposal (by the 'group of nine' competitors to Telstra) for deploying Fibre to the Node (FTTN) over existing copper access networks.

The paper draws attention to the trade-offs which the Howard government agreed to, in terms of the $1.1 billion in rural subsidies (the 'Connect Australia' project) needed to gain National Party support for the final tranche ('T3') of the sale of Telstra in 2005, which delivered a huge windfall to the federal Treasury. To meet further needs for rural areas, this was followed by an additional $600 million for a 'Broadband Connect Infrastructure Program'.

Darling points out that, in the two federal elections before 2007, the ALP's policy on broadband had been largely focussed on opposing the privatisation of Telstra, with only statements of general intent on the need for faster broadband. This changed dramatically on 21 March 2007 when the ALP's new federal leader, Kevin Rudd, announced his new national broadband network policy.

Darling concludes his paper with a detailed comparison of the Coalition and Labor policies on broadband leading into that year's federal election campaign.

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The Historic Paper

SPECIAL TUTORIAL PAPER

TOWARDS A BROADBAND POLICY

Peter Darling, Pondarosa Communications Pty Ltd

Under the Australian Constitution, matters relating to communications are a national responsibility. However, until recently, there had been a broad consensus across the political parties about most communications policies, with the major exception of the privatisation of the former incumbent, Telstra.

This consensus no longer holds. One of the issues raised by all sides in the recent election period was 'broadband', and there is no doubt that, now the election results are clear, Australia may actually be on the way to developing a broadband policy.

This article reviews the background to the recent policy debate, and provides some comment on the issues that have been raised in the Election Campaign.

INTRODUCTION

For many years, commentators have compared (unfavourably) Australia's laissez-faire approach to 'broadband' to that in many other countries.

Australians voted in a national election on Saturday 24th November, 2007 for all the positions in the House of Representatives (the 'lower' House) and half the Senate (the 'upper' House). The outcome of this election has resulted in a change of Government – the Australian Labor Party will form the Government for the next three years.

Under the Australian Constitution, matters relating to communications are a national responsibility. However, until recently, there had been a broad consensus across the political parties about most communications policies, with the major exception of the privatisation of the former incumbent, Telstra.

This consensus no longer holds. One of the issues being raised by all sides in the election period was 'broadband', and there is no doubt that now the election results are clear, Australia may actually be on the way to developing a broadband policy.

This article reviews the background to the recent policy debate, and provides some comment on the issues that were raised in the recent Election Campaign.

AUSTRALIAN TELECOMMUNICATIONS NETWORKS

In common with many countries, Australia had government-owned monopoly networks until the early 1990s – ***Telecom Australia*** for domestic traffic, and *OTC (A)* for international traffic. In 1991, the Government of the day combined these two carriers into a single company, ***Telstra***, and introduced limited network competition. The Government sold its domestic satellite operations to form a new carrier, ***Optus***, able to offer both fixed and mobile domestic service as well as international carriage. A third mobile licence (and associated GSM spectrum) was sold to ***Vodafone***.

These 1991 changes were the first step to full network competition, to apply from 1 July 1997. The ***Australian Labor Party*** (ALP) formed the government at the time of the 1991 changes, and through much of the preparation for the 1997 changes. Despite a change of government to the ***Liberal*** & ***National Party Coalition*** (LNP) in 1996, the same broad policy continued, and full network competition was introduced as planned in 1997.

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Over two hundred carrier licences have been issued,[1] with many small carriers (including ISPs) as well as the major carriers established in 1991. Telstra is still the largest (and most profitable) service provider.

THE PUBLIC SWITCHED TELEPHONE NETWORK (PSTN)

The telephone network provides service to almost all locations in Australia, and forms part of the global network. The PSTN is formed from interconnected, co-operating networks from a number of service providers. The network is optimised to carry a 4 kHz voice signal, but has also been used for other services working within this channel.

As was described in a previous TJA article (Darling 2005), the PSTN can be divided into

- The Core Network, made up of shared switched and transmission facilities, and
- The Customer Access Network or CAN that provides the connection from each user (customer or subscriber) to and from the core network.

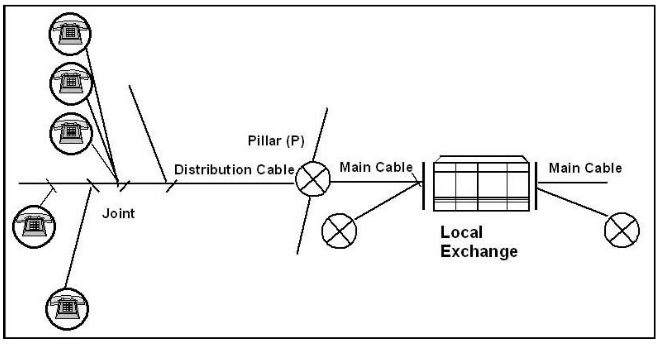

Figure 1 The customer access network

There has been continuous technical development of the core network, but very little change in the Customer Access Network for 'fixed' users. For almost all these users, the connection to the network is by a pair of copper wires, twisted to minimise interference to other wires, and incorporated into large cables that terminate at the local exchange, using a structure similar to that shown in Figure 1.

More recently, radio-based cellular techniques have been developed to support mobile telephony, providing telephony and other services to 'mobile' users, and there are now more mobile users than fixed users.

THE (PUBLIC) INTERNET

The network now known as 'the Internet' is formed from a set of interconnected networks based on the 'Internet Protocols' (IP) developed to interconnect different data networks. The Internet is defined by (transport) protocols rather than by its architecture or by the main service carried. Unlike the PSTN, where additional facilities and services are provided by network equipment (an 'intelligent network') the Internet only provides for the carriage of information (a 'dumb' network). Services are supported by applications running on the equipment at the network edge.

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The Internet Protocols were designed to support data carriage over a wide range of transmission media, with a wide range of transmission speeds.

CABLE TV NETWORKS

There has only been limited development of cable TV networks in Australia. In contrast to most other countries, the existing networks, using HFC (hybrid fibre-coaxial) technology are owned by the major PSTN operators. Optus started installing HFC networks in the major cities of Sydney and Melbourne in the mid-1990s, and this was matched by Telstra. The Optus network was used to support telephony as well as pay TV.

Changes in strategy by Optus stopped the extension of their HFC network, resulting in only a limited geographic coverage by their network and the matching Telstra networks. The major method of delivery of entertainment TV services is now by satellite rather than terrestrial cable.

OTHER NETWORKS

There have been other specialist networks, primarily intended for business users, with limited geographic carriage. These have included the telex network, an X.25 data network, a frame relay network as well as specialist point-to-point transmission networks.

AUSTRALIAN TELECOMMUNICATIONS POLICIES

Current communication polices in Australia have been developed to support the wide-spread availability of the telephone service, and allow for the introduction of competition in the provision of customer equipment, services and network facilities when in '*the long term interests of end users of carriage services or of services provided by means of carriage services*' (Trade Practices Act 1974).

UNIVERSAL SERVICE

Prior to 1990, the government-owned Telecom Australia was set the goal of extending telephone service across all geographic areas in Australia. When network competition was introduced, this was set as a direct policy to ensure that competition did not result in services only being provided in profitable areas. The current telecommunication legislation has the major Object '... *to ensure that standard telephone services, payphones and other carriage services of social importance are reasonably accessible to all people in Australia on an equitable basis, wherever they reside or carry on business...*' (Telecommunications Act 1997).

The mechanism for funding the provision of this universal service, the Universal Service Obligation (USO), has been a subject of continuing dispute since the introduction of network competition (and indeed is again being reviewed in late 2007). The services covered by the USO have been limited to telephony and equivalent services, for example TTY access for people not able to use the telephony service. Despite a number of proposals, there has been no agreement to extend the USO to cover other services[2] (such as broadband Internet), and it seems to this observer this would require a complete new basis for funding instead of the current PSTN-based system.

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NETWORK COMPETITION

Before the introduction of network competition in 1991, the incumbent carrier (Telstra) provided all services, and policies had to be developed to allow new entrants to interconnect with Telstra's services and facilities.

Whilst it was possible for a new carrier to provide competitive facilities in some areas, the new entrant generally had to use infrastructure and services already in place. This was achieved by a policy that allowed for services to be 'declared', either by industry agreement or by the competition regulator, the ACCC (Australian Competition and Consumer Commission). For these declared services, if commercial agreement could not be reached between the Access Provider (generally Telstra) and the Access Seeker, the ACCC was able to set access conditions, including a wholesale price.

The telephony Customer Access Network appears to have many of the characteristics of a natural monopoly. The high cost of infrastructure provision combined with the relatively low return from the capital invested means that there has been limited competitive provision of access infrastructure for the fixed telephone network, except in a small number of geographic areas with high business demand. This seems to be a situation where one firm can produce a given level of output at a lower total cost than can any combination of multiple firms – a natural monopoly. As a consequence, the fixed telephony access network has been regulated in Australia (as in many other countries) to ensure competitive suppliers of telephone service can use the CAN without having to pay the CAN provider excessive amounts.

TELSTRA PRIVATISATION

One of the major areas of difference between the two main political parties in Australia has been the ownership of the major carrier, Telstra. The ALP government established Telstra as a Corporation in 1991, but retained full Government ownership. The opposing political parties, which gained government in 1996, supported moving to full privatisation of the company.

Telstra was privatised in three stages. At each stage, there was political opposition to the sale of Telstra, and policy decisions were made to help overcome this opposition and assist passage of the enabling legislation through the Senate, in which the Government of the day often did not have a majority.

- The Bill for the sale of the first tranche of Telstra, T1, passed the Senate in December 1996, with a public share offering of one third of Telstra taking place from September 1997. Independent Senators from Tasmania and Queensland supported the sale, in return for specific benefits flowing to their States;
- After the success of the first float, the Liberal Party announced in March 1998 plans to sell the remaining parts of Telstra;
- A Bill to privatise the remaining portion of Telstra was defeated in the Senate in July 1998, with concern about the future availability of Telstra services, particularly in rural areas;
- In July 1998, the Government announced a staged approach:
    - Legislation for new customer service safeguards (to apply irrespective of any further changes in Telstra's ownership);

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- Further sale in stages, with the next stage (T2) leaving 51 per cent, and majority control, in Government hands; and
- An independent inquiry to assess Telstra's service levels to customers in each of metropolitan, rural and remote areas against prescribed standards before any further sale.

- After the LNP coalition won the October 1998 election, a Bill allowing for the next stage of the sale, and the creation of the Independent Inquiry was submitted and passed by the Senate in June 1999.
- The T2 share offering took place from September 1999
- The Independent Inquiry was established in March 2000, reporting to the Minister in September 2000. The Regional Telecommunications Inquiry (2002) found that users in metropolitan and regional centres enjoy good telecommunication services and are generally satisfied with them. They also found that a significant proportion of those who live and work in rural and remote Australia have concerns regarding key aspects of services.[3] These included lack of reliable access to the Internet and data speeds generally.
- The LNP was elected for a third term in November 2001, but it did not appear that there would be majority support in the Senate for further Telstra privatisation. At the start of the first Parliamentary session, the Government indicated that it would not proceed with any further sale of Telstra until it is satisfied that arrangements are in place to deliver adequate services to all Australians.
- An Inquiry into regional telecommunications services was established in August 2002, reporting in November 2002. While the Inquiry report was generally positive about rural services, it noted general availability of dial-up Internet access, but concerns about access speeds (Regional Telecommunications Inquiry 2002).
- The LNP Government was returned in the election of October 2004, and for the first time had a majority in both Houses of Parliament. A revised Telstra (Transition to Full Private Ownership) was introduced into Parliament in September 2005.
- There was concern in the junior member of the coalition, the National Party, about the impact of the full sale of Telstra on users in rural areas. The Government agreed to use the proceeds of the Telstra sale to establish a $2 billion Communications Fund, which would be accompanied by a $1.1 billion Connect Australia package to extend access to, and improve the affordability of broadband.
- With these assurances, the legislation was passed by the Senate. The final tranche of the sale of Telstra (T3) proceeded, and the shares were listed on the Australian Stock Exchange from November 2006. (Some Telstra shares remained in Government ownership, via the Future Fund established by the Government to support public sector superannuation.)

Telstra was (finally) fully privatised as a single company, and the ability of the government to use its role as majority shareholder to encourage the company's decisions removed. A large amount of current policy has come from the political decisions necessary to enable the sale. Other options, such as the structural separation of the company, did not seem to find any favour during these political processes.

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SUPPORT FOR USERS IN RURAL AND REMOTE AREAS

As can be seen from the long tale of Telstra privatisation, the need to provide 'adequate' services to users in rural and remote areas has been a continuing concern.

With a government-owned monopoly, government direction may be sufficient. In a competitive market place, there is no certainty of service provision across all areas. As described above, the introduction of network competition required other policy mechanisms – for example, the Universal Service Levy.

During the process of Telstra privatisation, three further policy approaches were adopted:

- The requirement for special action by Telstra, often as a condition of Telstra's Licence or by specific legislation. Examples include the requirement for untimed local calls, and the availability of a digital data service.
- The expenditure of Government money (often from the proceeds of Telstra privatisation) to meet a particular need, for example the extension of mobile coverage in particular areas to the subsidy of services provided by an ISP in a remote or rural area. These approaches are often linked together in some form of programme – for example, *Networking the Nation* or *HiBis*. However, to many observers, they lack cohesion and seem subject to the political advantage of the allocating party.
- The adoption of broader policy frameworks to support specific goals. In the view of this observer, this approach has yet to be fully realised. The recently established **Communications Fund** is intended to '*… provide an income stream to fund the Government's response to reviews of the adequacy of telecommunications services in regional, rural and remote parts of Australia prepared by the Regional Telecommunications Independent Review Committee*' (Commonwealth Numbered Regulations 2005). This should provide the possibility of a more wholistic approach, to meet the stated goal of future-proofing rural communications, but would not prevent election-driven fund allocation. Similarly, the **Connect Australia** programme should provide the possibility of longer-term, goal driven allocation of funds.

THE MOVE TO BROADBAND

WHAT IS (OR ISN'T) BROADBAND?

What is the 'broadband' that is now being quoted in political speeches and discussions?

The term is very general, with no accepted definition. In general, when people are talking about 'broadband', they seem to mean 'broadband internet access'. As I will argue later, this is a rather limited definition.

To the **OECD**, in their oft quoted broadband rankings, the OECD Broadband Statistics, broadband download speeds are 256 kbit/s or higher (OECD 2007).

For the **FCC**, download speeds of 200 kbit/s or more are broadband.

For the **ITU**, broadband describes data at rates greater than the ISDN Primary Rate (1.54 Mbit/s or 2.048 Mbit/s).

It often seems that, to a **marketer**, broadband is any speed faster than dial-up!

To this **writer**, who lives in a rural area without ADSL, the more general definition could be 'an access speed at least twice the speed currently available'!

Figure 2 Dialup is not broadband

BROADBAND TECHNOLOGIES

An article in the recent special Broadband Edition of this journal summarised the technologies that are in use or planned to provide broadband (Darling 2006a).

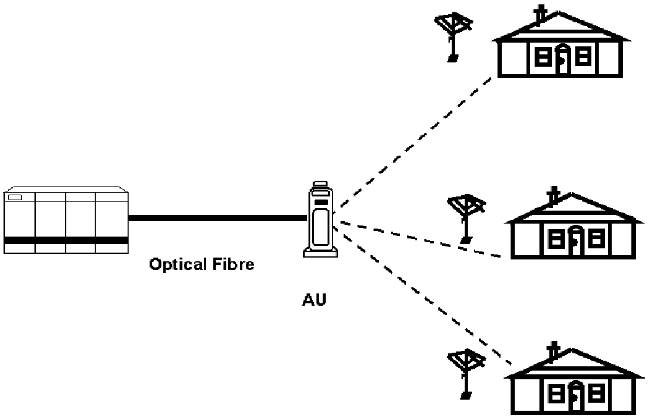

Figure 3 Broadband CAN

Optical Fibre is the preferred technology in the Core Network, supporting data speeds up to and including Tbit/s rates. Traffic from a number of users can be combined over the Core Network, but at as shown in Figure 3, at some point close to the user there has to be a unique connection established for each user.

This 'Access Unit' could be, for example:

- The subscriber stage of a telephone exchange;
- A remote node (RIM or CMUX) in the telephone network;
- A mobile base station;
- A wireless data access point, or
- An Internet router/server/access point.

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As described in the previous article, possible technologies to provide a broadband access link include:

- Coaxial cable: for example, over a cable TV network;
- Copper: using the current telephony copper access network, using DSL (Digital Subscriber Line) technology;
- Terrestrial Radio: including the next generation broadband systems;
- Satellite and Tethered Stations: radio access from geostationary satellites, position keeping platforms or by constellation of satellites in other orbits;
- Distribution by Powerline: over the mains power line, with high frequency signals superimposed over the 50 Hz (or 60 Hz) power distribution; and
- Optical Fibre: using techniques such as Passive Optical Networks to reduce infrastructure cost.

With some technologies, the connection to a user may be over a single transmission medium dedicated to that user, for example over a copper pair in the telephone network, or a dedicated optical fibre. With other technologies, a shared transmission medium may be used, for example a radio-link from a base station or a power-line distribution system.

As a general rule, the closer the Access Unit (and optical fibre termination point) to the user, the higher the speed that is possible. When a shared transmission medium is used (for example a radio-based system) the available speed will depend on the number of users at any time, and the nature of their use. For example, users with constant speed applications such as video streaming are restricted to a simple division of the total bandwidth available, but users with varying 'bursty' traffic typical of Web browsing will have much higher peak speeds.

SERVICE REQUIREMENTS

There is no ideal broadband speed – the required speed is determined by the required applications:

- For **email**, and **very simple web browsing**, **dial-up access** is sufficient
- For **voice** and (low resolution) **video telephony**, for low resolution video conferencing, and more complex web browsing, **medium speed broadband access** (up to 750 kbit/s) is needed. (eg ADSL)
- For **image rich web applications**, **medium to high speed broadband access** is needed (e.g. fast ADSL or ADSL2+)
- For a **single broadcast-quality TV channel**, **medium to high speed broadband access** is needed (e.g. fast ADSL or ADSL2+)
- For a **single broadcast-quality high definition channel**, **high speed broadband access** is needed (e.g. ADSL2+).
- For **multiple TV channels**, and **personal video recorder** functions, **very high speed broadband access** is needed (e.g. ADSL2+ or Optical Fibre).

The consultant *broadbandtends.com*, looking at the developing US broadband market, suggests:

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- For a 'basic triple play' of 2 SDTV, Internet, telephony, a speed of 6 Mbit/s or greater was necessary; but
- To move to HDTV, video on demand and personal video recording, the user would need 20 Mbit/s initially, 100 Mbit/s later.

These higher speeds are suggested for a service provider combining the functions of entertainment provision (Pay TV), Internet service provision and telephony service provider, with multiple applications in use in a household.

To this observer, the key questions must be what do users/customers want, and how much are they willing to pay? Will there be other applications (not yet defined) that will be valued by users and justify the cost of very high speed broadband access? Would other technologies (e.g. satellite distribution) be more cost-effective?

BROADBAND IMPLEMENTATION IN AUSTRALIA

Services at broadband speeds (for example 2 Mbit/s) have been available to business users for some time, but residential broadband has only been widely available in this decade.

Prior to this, residential access to the Internet was via a dial-up connection over the PSTN to an Internet Service Provider (ISP). When the core of the PSTN was updated with digital technology, and as modem technology improved, speeds up to 56 kbit/s became possible, but this was the limit of the technology (and could rarely be achieved in practice).

The first residential broadband Internet access was provided over the Optus and Telstra HFC networks installed for Pay TV, at first using proprietary technology with cable modems provided by the carriers, and later using the internationally standardised DOCSIS (Data Over Cable Service Interface Specifications).

While the HFC networks are still used for broadband access, the major broadband technology in current use is DSL (Digital Subscriber Line), in particular asymmetric DSL (ADSL) with a faster download speed (from the network) than the upload speed. This technology makes use of existing copper pairs, provided for telephony service, with frequencies above telephony providing broadband access.

The first set of ADSL standards provided for download speeds of up to about 5 Mbit/s for users close to the exchange – the speed available drops rapidly with distance from the exchange, or less than perfect cable condition. Later standards increased this speed – the ADSL2+ standard allows download speeds over 10 Mbit/s at distances of up to 2 km from the exchange, while the VDSL+ standards allows speeds of over 100 Mbit/s over short distances.

The competition regulator, the ACCC, declared the 'Unbundled Local Loop' or ULL service in October 2000. This allowed another service provider to install their own DSL and telephony equipment at a Telstra exchange, and use an existing Telstra copper pair to provide service to their customer. The ACCC further declared the 'Line Sharing Service' in December 2004, allowing another service provider access to the higher frequencies on an existing copper pair while Telstra continued to provide telephony service over the line.

Initially, the DSLAM equipment required in exchanges was large and complex and was mainly provided by Telstra. Other service providers bought the Telstra service at a wholesale price. As DSL technology evolved, DSLAMs became smaller and much less expensive. This has resulted

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in a number of service providers installing their own DSLAMs in Telstra exchanges, and rapid growth in services in use.

According to the figures from an Australian Bureau of Statistics Survey in June 2006, at that stage over half the Internet services were provided by broadband access, and this proportion would have increased with the continuing rapid growth in Broadband Internet since that survey (ABS 2006). The survey also indicated that broadband Internet connections were much more common in metropolitan areas (34% of all households) than in non-metropolitan areas (19% of all households).

BROADBAND 'LEAGUE TABLES'

While there was rapid growth in the number of broadband access services in use of Australia, many commentators noted that we were well below the penetration rates of comparable countries, especially those such as South Korea which had a central policy promoting the availability of broadband access and the services that could be used over broadband.

Information such as that summarised in Figure 4 from the OECD Broadband Statistics entered into the public debate on communications policy – why were we so low in the rankings, and did it matter.

(To be fair, the latest OECD figures show that, at December 2006, Australia was now ranked as no. 16, having passed Austria and Germany, and just behind the USA [OECD 2007]. However, our average speed lagged behind many other countries, including these. If and when the OECD raises its minimum standard from 256 kbit/s, we may drop to almost the bottom of the rankings.)

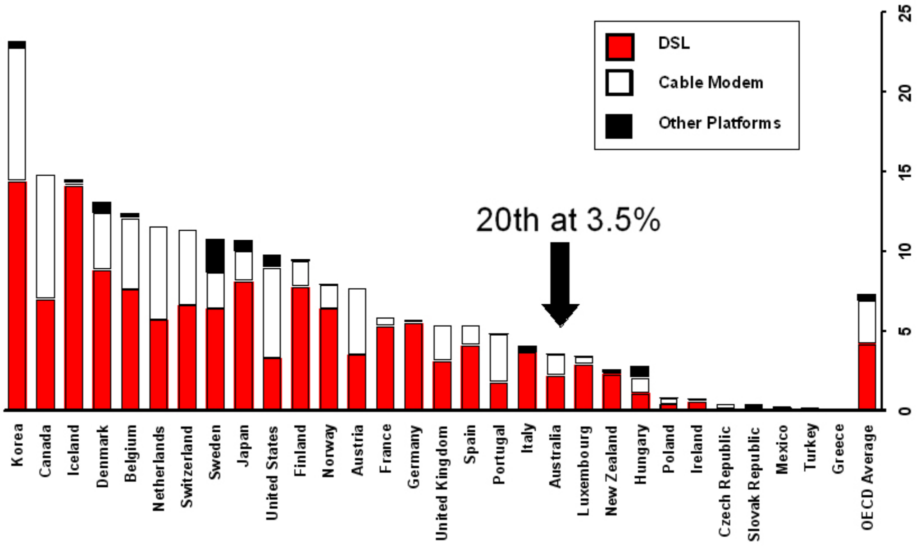

Figure 4 OECD rankings
Source: OECD

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INDUSTRY PROPOSALS FOR BETTER BROADBAND ACCESS

Over the last two years there have been two competing proposals from the industry to provide widespread 'next generation' broadband access.

TELSTRA'S BROADBAND PROPOSALS – NOVEMBER 2005

Telstra conducted a series of public Strategy Meetings in November 2005 outlining proposals for major changes to their networks, as summarised in a previous TJA article (Darling 2006b).

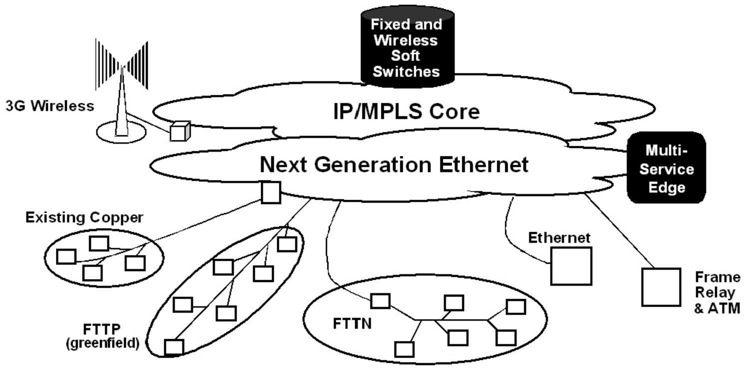

Figure 5 Telstra's Proposed Network

Telstra announced plans to replace their core network with Internet Protocol based technology, and to provide medium to high speed broadband access for users in major cities and towns.

For 'Greenfield' areas they indicated they planned to use optical fibre to the user's premises (FTTP). For areas with existing copper, they would use ADSL2+ over copper.

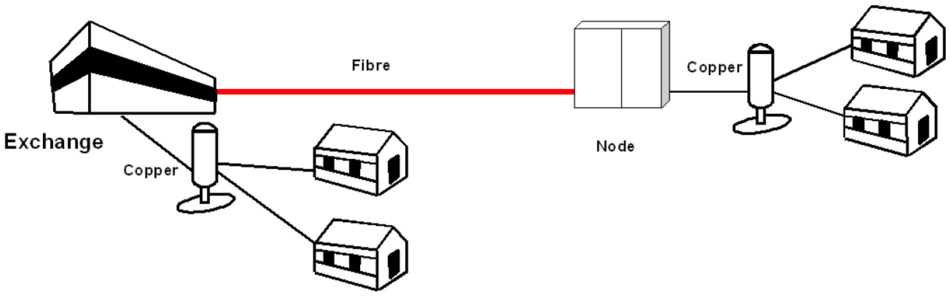

Figure 6 Fibre to the Node

For one third of users, this would come from equipment at the current exchange site. For the remaining two thirds, the ADSL equipment would be installed in road-side cabinets or 'nodes' which would be served by fibre from the core (hence fibre to the node or FTTN). This approach was claimed to be able to provide download access at 12 Mbit/s or greater.

Telstra's strategy presentation suggested that their proposed access strategy was 'subject to acceptable regulatory conditions'. In answer to analysts' questions, Telstra gave a general indic-

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ation that they planned to restrict competitor's access to ensure that Telstra gained maximum value from their investment.

Under the current policies and regulatory arrangements this seemed very unlikely. The proposed Telstra broadband access network would almost certainly become a 'Declared Service', and Telstra would be required to provide access at rates set by the ACCC, which would certainly result in a lower return on investment than Telstra required.

Telstra lobbied the Government to provide a 'safe harbour' for their investment, allowing regulatory relief from providing access to their competitors under current conditions. Telstra's competitors lobbied the Government against this approach, indicating that not only would their ability to compete be reduced, but also the introduction of Telstra nodes to two thirds of users would mean competitors could no longer use existing and planned exchange-based DSL equipment.

TELSTRA PROPOSAL TO THE PREVIOUS GOVERNMENT

The Telstra internal proposals covered the major metropolitan areas only. They proposed to the Government a broader national approach, the details of which have not been generally released. Based on information provided at a Senate Committee,[4] the Telstra plan was to replace ageing parts of the old copper network and to connect 98 per cent of Australian homes and businesses to fast broadband over five years. Telstra proposed to expend $3.1 billion of its own funds, with Government contribution of $2.6 billion. Part of the Telstra proposal included relaxation of the regulatory rules.

At the same Committee, the Department of Communications, Information Technology and the Arts gave the following reasons for rejecting the Telstra plan:

- significant winding back of the competition regime;
- an effective access holiday for the new network;
- no commitment to pricing;
- effectively locking the Government into Telstra's technology choices;
- risk of further increasing Telstra's dominance;
- funding based on a significant Government contribution; and
- no leveraging of private sector investment.

There were a number of reports in the media of continuing discussions between Telstra and the Government, and between Telstra and the ACCC, but these were not successful. Telstra issued a statement to the Australian Stock Exchange on 7th August 2006 indicating that the fibre-to-the-node talks with the ACCC had been discontinued and that '... *Until Telstra's actual costs are recognised and the ACCC's regulatory practices change, Telstra will not invest in a fibre-to-the-node broadband network*.'

From discussions within industry groups, it appears that Telstra had modified its plans from their original proposals, removing many of the original objections. They had agreed to an open-access network, and proposed more extensive use of VDSL to give higher access speeds.

The financial areas remain unresolved.

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G9 PROPOSALS

The G9,[5] a group of nine competitors to Telstra, proposed an alternative plan for broadband access with has technical similarities to Telstra's plan, but with considerable organisational differences.

The group released its proposed Fibre-To-The Node (FTTN) network model,[6] and has lodged a special access undertaking with the ACCC.[7] They propose to create an industry-owned, special purpose company, SpeedReach, to make key decisions about the network, and a new entity created called the Fibre Access Network Operating Company (FANOC), which would manage the network.

The G9 planned to use a FTTN structure similar to that proposed by Telstra, with the majority of users served by DSLAMs at Nodes located beyond the local Telstra exchange. As the G9 has confirmed, this proposal would only work if Telstra uses the G9 network and Telstra grants access to G9 to the Telstra copper mid-span. This would require Telstra's co-operation or regulatory intervention – not surprisingly, Telstra has indicated it would fight what it sees as confiscation of its assets.

A key area of difference was that the network owner FANOC would provide wholesale services only. Under the G9 proposal, no single carrier would be allowed to own FANOC, and FANOC would not be able to provide retail services.

The biggest barrier to the G9's proposal is that a significant portion of the existing copper network will still be required, but this is owned by Telstra. The G9 claims that Telstra would be able to join but Telstra has declined the invitation!

BROADBAND POLICIES – AUSTRALIA'S MAJOR POLITICAL PARTIES

Many of Australia's trading partners in our region have seen the development of a national communications infrastructure as a policy priority, and have invested to achieve this either directly, via Government funding, or indirectly, by using policy tools such as regulation to encourage industry investment.

As a consequence, the OECD listing of broadband penetration showed Australia with a much lower ranking than countries we would consider our peers. This has resulted in pressure on both major parties to develop a coherent broadband policy.

SENATOR ALSTON (THE WORLDS GREATEST LUDDITE?)

Senator Richard Alston,[8] the Minister for Communications in successive LNP governments from March 1996 to October 2003 was often dismissive when asked about the need for an Australian broadband policy. He appeared to doubt the benefits of widespread availability of broadband, and in interviews in 2002 was critical of the South Korean broadband initiative, indicating he believed it was the main reason for the high take-up rate was pornography and gambling!

His view seemed to be that demand was uncertain, and that if it existed, the market would deliver, assisted by the regulatory settings put in place from 1997.

Others were not so certain, and from about 2000 there began to be calls for a new policy framework going beyond the 1997 telephony-oriented policies. In March 2002, Senator Alston announced the formation of the *Broadband Advisory Group*, composed of high-level people from the ICT industry and chaired by the Minister himself.

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The Group reported in January 2003, making 19 Recommendations, emphasising the benefits of broadband and the need for a broadband vision matched by a set of goals, and made specific implementation recommendations.

It may be a little unfair to say that very little happened – perhaps it is true to say that what did happen, happened very slowly. Senator Alston did not seem to have a change of heart.

RURAL AND REGIONAL CONCERNS

A significant proportion of the proceeds of the T1 and T2 sales were used to support programs such as 'Networking the Nation' that assisted basic (dial-up) Internet access, mobile telephony, fixed telephony and related issues in rural and regional Australia.

By the early 2000s, technology to provide broadband started to be offered (e.g. cable modems, ADSL). It was notable that availability was much higher in metropolitan areas, and there was concern from members of the junior party of the LNP Coalition, the National Party, that this digital divide would continue, particularly if and when Telstra was privatised.

The Federal and all State Governments, with the exception of Victoria, agreed to a **National Broadband Strategy** in March 2004, which was designed to '*inform future policy development in broadband and coordinate activities across government. It sets a number of objectives for broadband development in Australia.*' One of the more tangible outcomes from this was **HiBIS** (Higher Bandwidth Incentive Scheme) which subsidised ISPs on a per eligible user basis to offer higher speed broadband access in regional and rural areas. While this did support some provision of faster access, it was only a short term solution, causing problems when the program ended in December 2005. HiBIS was extended by the **Broadband Connect** program, which was in turn extended by the **Australian Broadband Guarantee** announced in March 2007.

In 2005, the Page Research Centre, a policy group associated with the National Party, published a Discussion Paper[9] developed as part of the discussion at that time about the final privatisation of Telstra. This paper described an option for a government-provided optical fibre CAN, replacing the existing copper CAN, to all but 6000 remote users in rural Australia. It quoted an estimate prepared by the construction company Baulderstone Hornibrook that that this would take $7 Billion over five years, but noted that Telstra's costing at that time was closer to $30 Billion over 20 years.

TOWARDS A BROADBAND POLICY

By 2005, with the final sale of the last tranche of Telstra, there was increasing pressure on the LNP government to develop policies covering broadband, particularly for rural areas where the need was seen to be greatest (and the political pressure greatest).

As part of the agreement to ensure passage of the T3 legislation, the Government agreed to establish **Connect Australia**, a $1.1 Billion package for regional access to telecommunications services. As well as continuing the case-by-case approach of HiBIS, the Minister announced the Broadband Connect Infrastructure Program.[10]

BROADBAND CONNECT INFRASTRUCTURE PROGRAM

Programs such as HiBIS showed the need for better underlying infrastructure to provide rural and regional communications, rather than a drip-feed of funds to many different service providers

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using different and often incompatible technologies. The *Broadband Connect Infrastructure Program* was designed to support 'a small number of large scale infrastructure projects', and in fact is now planned to cover only one inter-related project by one provider.

The Government announced that $600 million would be allocated to the project, and after public discussion it called for expressions of interest in June 2006. It sought information on possible approaches to provide improved broadband coverage in under-served areas, requiring improved multi-megabit broadband speeds and a technology platform that would be scalable, including the capacity to achieve even higher speeds into the future.

The details of the contract that came from this program are described in following sections.

'THE BROADBAND BLUEPRINT'

The Minister, Senator Coonan, released a document titled **'the Broadband Blueprint'** in December 2006. It was released as part of a joint Australia-Korea-New Zealand Broadband Summit, and according to the Departmental website the document was intended to:

> provide a national framework for the future of broadband in Australia. In order to establish this framework the Blueprint gives an overview of the Australian Broadband Market as at December 2006. It also details the past and present initiatives to encourage broadband implemented by the Australian Government as well as a brief overview of the activities of state, territory and local governments. The Blueprint articulates the essential elements of the broadband market and a forward strategy to encourage their development (Australian Government 2006).

The following extract from the Table of Contents in the Blueprint outlined the 'strategy' that was promised in the website.

FUTURE ACTIONS

- *Continuing collaboration with all tiers of government*
- *Learning from international experience*
- *Guidance for local councils and planning authorities*
- *awareness campaign on use and consumer opportunities*
- *Mapping backhaul*
- *Spectrum*
- *Measuring progress*
- *Reviews*
- *Conclusion*

And what was the planned Strategy? To quote from the final section of the Conclusion:

> For its part, the Australian Government will continue to provide leadership to shape Australia's broadband future and will foster investment confidence through a stable yet responsive regulatory environment and targeted investment to areas of market failure and need.

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To this writer and many other observers, this document was embarrassing. It was over-produced, and it considerably under-delivered. This 'strategy' could not stand comparison with the initiatives from South Korea, or even New Zealand.

CURRENT POLICIES AND POLITICAL DEVELOPMENTS

THE SITUATION IN 2007

By the start of 2007, there was much discussion but little action about future broadband:

- Medium speed broadband, primarily ASDL but also DOCSIS over pay TV cable, was available at in most metropolitan area and some larger non-metropolitan towns;
- Some competitors to Telstra had started to install faster ADSL2+ equipment at major exchanges, and to provide service. Telstra was also reported to have installed ADSL2+, but said it would not provide service in the current regulatory environment;
- Telstra had outlined its strategy to provide faster broadband, but had failed to gain agreement with the Government and ACCC for changes to the regulatory environment that Telstra believed were necessary before it could make the necessary multi-billion Dollar investment;
- The G9 had outlined their strategy for a FTTN high-speed broadband system, but it was obvious this could not proceed without Telstra involvement (or Government direction to Telstra);
- The LNP Government was developing arrangements to provide low to medium speed broadband in rural areas, via the Broadband Connect Infrastructure Program;
- Telstra had been privatised, and Telstra management was taking a much more aggressive stance to defend what they saw as their shareholder value. Relations between the company and the government were very different from those that had applied in the past, were a government suggestion became Telstra policy.

Both in Australia and other countries, it was clear that moving to the next stage of broadband, and indeed to the 'Next Generation Network' concept of integrated and converged communications would take major investment. The copper telephone access network was never designed for broadband, and ADSL technology was reaching its limits. Higher speeds and more reliable service would require investment to move the Access Unit closer to the end user. Around the world, service providers were developing new networks, using either fibre to the premises, or fibre to a Node near the premises, often in competition with high speed access over entertainment TV cable.

A NEW ALP POLICY

At the previous two elections, the Australian Labor Party had made general remarks about the need for faster broadband, but their detailed policies were more concerned with opposing the sale of the final tranche of Telstra. In his response to the Budget in May 2006, the then Opposition Leader made reference to a possible national plan for a 6 Mbit/s network, but like most of the previous broadband discussions, this seemed just another general statement of intent.

On the 21st March 2007, this changed.

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The new leader of the ALP, Kevin Rudd, announced a new policy **'Building a National Broadband'** (Australian Labor Party 2007). The new policy said that a future ALP Government would '*build a world class national broadband network, providing service for 98 per cent of Australians*', over a five year period.

The ALP said they would invest up to $4.7 billion in this proposal, in a partnership with the private sector. They said the result would be a joint venture, most likely 50% owned by the Government. They indicated that the private sector partner would be chosen by a competitive process with potential partners such as Telstra and the G9 bidding for access to the joint venture.

The network would be 'open access', providing wholesale services to all service providers.

The statement indicated that 'an appropriate regulatory framework' would be part of the discussions during the choice of partner.

The source of the Government contribution of up to $4.7 billion would be the existing communications fund (which would provide $2 billion), with the remainder taken from the Future Fund's 17 per cent share of Telstra.

A NEW LNP COALITION POLICY

The Minister, Senator Coonan, announced a new policy framework **'Australia Connected'** on 18 June 2006,[11] in a move seen by many as a response to the ALP proposals.

She included the previous initiatives announced by the Government, including the regional wholesale network funded by the *Broadband Connect Infrastructure Program* and the 'top-up' scheme *Australian Broadband Guarantee* which provided a broadband subsidy of $2750 per household for the areas most difficult to reach. As described below, she included details of the successful tender for the *Broadband Connect Infrastructure Program* as part of the package of announcements.

Her major new initiative was the announcement of **a new commercial fibre-optic network**. This was designed '*to facilitate a fibre network build in cities and larger regional centres via a competitive bids process and subsequent enabling legislation*'.

She announced the establishment of an **Expert Taskforce.** Unlike the large number of previous taskforces/d committees, this would not just make recommendations to Government (which would often then be ignored) but had a more specific task. The Minister indicated the '*the guidelines for the competitive bids process will be developed by the Expert Taskforce in consultation with industry. The Taskforce will also settle a realistic timetable for the bids to be submitted and assessed.*'

The Minister emphasised that her plans would not involve expenditure from the Communications Fund, the revenue from which would still be available for future rural upgrades.

THE LNP RURAL PROPOSALS – THE OPEL WHOLESALE NETWORK

As part of the LNP broadband package, Senator Coonan and the Prime Minister announced on that a new company, **OPEL**, a joint venture wholesale company between Optus and Elders, was the successful bidder for the Australian Government's $600 million Broadband Connect Infrastructure program. They also announced that the Government would allocate a further $358 million to enable the OPEL network to be extended, resulting in a claimed provision of high speed broadband to 99 per cent of Australians.

The network build would include:

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- 15 000 kilometres of fibre optic cable open access backhaul to link rural areas to major cities;
- Enabling 312 exchanges with ADSL2+, with an additional 114 exchanges being enabled by Optus on a commercial basis, providing ADSL service to users in or near major towns;
- The rollout of 1361 new wireless broadband 'WiMax' sites across the country, to serve users beyond the approx 2 km reach of the ADSL2+ services.

The Minister's announcement indicated that the first services were expected come online in September 2007, with the entire network completed by 30 June 2009.

Many commentators expressed major concerns about the WiMax component of this initiative. WiMax is not yet a fully mature standard,[12] and it appeared that OPEL intended to use the earlier 'Fixed WiMax' standard rather than the 'Mobile WiMax' standard which is likely to have greater international use. Also, it seemed that OPEL planned to use unlicensed spectrum in the 5.8 GHz region. This is a very high frequency for rural use, and by comparison (for example) with Telstra's NextG HSPDA service at 850 MHz, coverage in hilly areas would be restricted (as the writer knows from personal experience, living in a hilly rural region beyond ADSL reach with little or no mobile coverage).

The Minister's claim of 12 Mbit/s coverage (not *up to* 12 Mbit/s) for users served by WiMax does not seem realistic, and indeed the more detailed coverage information on the DCITA website has many disclaimers. In the view of this writer, the WiMax service is likely to achieve speeds of much less than 12 Mbit/s for most users, and may leave many areas unserved because of radio propagation problems.

THE EXPERT TASKFORCE

Following its establishment with the Minister's Statement in June 2007, the Expert Taskforce (ETF) issued draft Guidelines for public comment (Expert Taskforce 2007a). These guidelines indicated that the Taskforce was looking for proposals for the roll-out and operation of a privately funded, open access, high speed broadband network infrastructure in Australia's capital cities and major regional centres.

The proposals were expected to indicate the requirements for legislative or other regulatory changes, designed to directly assist the proposal. They were also to indicate proposed arrangements to provide for appropriate compensation to affected parties.

There was substantial public comment, focussing on the tight time-frame, the evaluation procedure and criteria, and the limitations of the network to only serve major centres. The Taskforce made some changes to the timescale, but preserved the broad direction of its approach.

On 20 September 2007, the Taskforce called for proposals for the commercial roll-out of new open access high speed broadband network infrastructure and services, in accordance with its Guidelines for High Speed Broadband Network Infrastructure Proposals (Expert Taskforce 2007b).

The closing date for Proposals set by the Taskforce is 14 February 2008. The proposals will be issued for public comment from 21 February until 17 April.

It is, of course, likely that new government elected on 24 November 2007 will vary these arrangements.

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HOW WILL WE USE BROADBAND?

As mentioned earlier in this article, there are two main public communications networks – the Internet, and the PSTN. One of the writer's major concerns is that almost all that has been written about broadband is really about the broadband Internet, and broadband should be much more than that.

While the Internet is of increasing utility, the telephone network remains the most socially important network. This role is not likely to reduce, and indeed has been increasing as mobile access to the PSTN, for voice and text, has become ubiquitous. As the writer outlined in an earlier TJA article, the technology of the two networks is converging, but one is not a direct replacement for the other (Darling 2004). Table 1 gives a brief summary of the characteristics of each network.

	Public Switched Telephone Network	Public Internet
Technology	Designed to carry voice, evolving to carry 64 kbit/s circuit switched digital. Underlying technology moving to Quality of Service enabled packet (IP).	Designed to transport end-to-end data packets across the network.
Reliability and Quality	Designed for high reliability and quality of service, in both component elements and network architecture.	Designed as a 'best endeavours' network, with no guarantee of data delivery. Quality may be enhanced by end-to-end protocols such as TCP, but for real-time interactive traffic such as voice this approach cannot be used.
Flexibility	Relatively inflexible, limited by low bit rate architecture.	Flexible, able to work over a very wide bit-rate and to support new applications and services over standardised interfaces.
Regulation	Strongly regulated at the national level, and by international agreement. The telephone service is regarded as having high social importance in almost all countries, and many of its characteristics are set by national governments	Lightly regulated, with many aspects set by national agreement in technical bodies such as the IETF. Increasing content regulation.

Table 1 Comparison of PSTN and Public Internet

The public Internet, as currently implemented, is not able to support a telephony service that meets current national regulatory requirements. The bit-rate requirements to support telephony are low, but the quality requirements high.

The telecommunications industry has developed the concept of the '**Next Generation Network**' or **NGN**. Such a network would be packet based (almost certainly using the Internet Protocols),

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with necessary extensions to give a level of service equal to or better than current carrier networks, with the flexibility of the current Internet, and providing a full range of data transmission speeds.

The NGN is already developing from the move to packet-based technology in the current PSTN.

As the multi-billion dollar investments are planned, all services, including telephony, must be taken into account. It would be almost unthinkable to develop a broadband access scheme only suitable for broadband Internet, and having to retain a complete duplicate telephony infrastructure.

A CRITICAL LOOK AT THE TWO PROPOSALS

Two points will strongly influence future policy implementation:

- Telstra was privatised as a whole. The company (or more correctly the Telstra shareholders) own both the access network and the core network, as well as the services provided over them;
- The proposals now being considered by both parties, in whole or part, rely on the use of sections of the Telstra copper access network to carry broadband traffic.

As a consequence, any plan that is agreed has to take into account the implications on Telstra's current networks.

COMMON POINTS

The following looks at common points in the two policy proposals.

As described, **they rely on the use of fibre to the node**. This means that the broadband provider would use Telstra copper for the final link to the user, and access the current copper at some point, probably relatively close to the end-user.

This has considerable operational implications. ADSL from the exchange site would not be feasible where a node has been provided, both for technical reasons (the much higher power level needed from the node to gain maximum speed) and for operational reasons (as it may be better to terminate the copper at the node).

If Telstra is the successful tenderer, they would gain considerable operational benefits by fully providing a digital connection to all users, even if a user does not choose broadband. If the system were properly specified and integrated with back-office systems, most upgrades, downgrades and changes could be done without physical intervention, and there could be continuous fault analysis and quick rectification.

If Telstra was not successful, many regulatory changes would be necessary to ensure success. As the G9 has already suggested, Telstra would have to be prevented from overbuilding with its own FTTN. If this was permitted, Telstra would have operational advantages and would legitimately be able to place the interests of maintaining its own assets above that of the other broadband access provider. Telstra is already using nodes (RIMs and CMUX) in its network to provide telephony and ADSL, and the regulatory/legislative problems to be solved would be very substantial. If Telstra did not co-operate, there would have to be the potential for considerable litigation.

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Even if Telstra volunteered or was forced to use the new broadband provider, it would still have to provide a copper CAN for its customers. The new broadband provider would not have the operational advantages mentioned above, and the provision of broadband for an individual user would require co-ordinated manual action by both Telstra and the broadband provider.

If Telstra was not the chosen broadband provider, the selected provider may well find the use of some other technology more appropriate, for example fibre to the premises, or a final link from the access unit to the user by radio, or an electricity powerline.

THE LNP PROPOSALS

RURAL AND REGIONAL

The LNP proposal has already commenced implementation, with the OPEL contract signed on 10th September. As outlined previously, the provision of service to areas outside towns is likely to be less robust than the ALP coverage, with possible gaps in coverage due to terrain and radio propagation problems. Users served by ADSL2+ may be able to be upgraded to NGN, but there is no indication this has been contemplated in the work so far.

MAJOR CENTRES

As indicated above, the work being carried out by the Expert Taskforce should be broadly compatible with the ALP proposal, with the common problems also being outlined above.

As there will be no payment to successful bidders, the only benefit they would receive would be the easing of regulatory restrictions.

It has been reported that the G9 had said they would bid, that Telstra was considering its options and the Deutsche Telekom Asia, with Babcock and Brown, may bid.[13]

If the LNP Coalition had been returned, there would have still been many legislative, regulatory and legal issues to be resolved, particularly if the contract was to be awarded to someone other than Telstra.

THE ALP PROPOSAL

Following the election of an ALP Government, this proposal will form the basis of future broadband development. Unfortunately, little detailed information was made available about the ALP proposal prior to the election. Their approach seems to be based on the proposal put by Telstra to the previous Government in late 2005/ early 2006. As described earlier, that Telstra plan was to replace ageing parts of the old copper network and to connect 98 per cent of Australian homes and businesses to fast broadband, using FTTN technology, over five years. Telstra had proposed to expend $3.1 billion of its own funds, with Government contribution of $2.6 billion (total of $6.7 billion).

The ALP proposal was also for a similar 98% coverage, with a Government contribution of up to $4.7 billion, matched by a similar amount from the private sector (total of up to $9.4 billion).

In media discussions during the election campaign, the ALP indicated that it would not be releasing any coverage maps. The ALP spokesman Senator Conroy was reported as saying 'The network configuration is drawn from commercial in-confidence information that Telstra, understandably, will not allow us to publish' (Sainsbury and Hart 2007)

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The proposal is based on use of a FTTN structure in rural areas. This would be more robust than a wireless solution, and better placed to be part of an NGN, but the higher cost of FTTN in areas with lower population density would probably mean the use of equipment to the more robust ADSL2 standard, resulting in service over a greater distance but at lower maximum speeds than obtainable from ADSL2+.

Now the ALP has won Government, it has two basic questions to resolve:

- How does the current contract with OPEL impact its plans? In particular, should the WiMax component be replaced by FTTN? Users receiving WiMax broadband will have to retain their Telstra copper-based services, as WiMax would not be appropriate to provide reliable telephony service. **This is incompatible with the NGN Concept, and would restrict these users from access to future NGN services.**
- How compatible will the work already done by the Expert Taskforce be with the ALP approach? (To this observer, there would seem to be considerable overlap, but significant areas of detailed difference, such as the planned coverage).

CONCLUSION

There is no doubt that Australia is now on the path to a policy supporting a next generation broadband network, but now that the election result is known, much implementation work needs to be done

The policies of the two major parties had many similarities, particularly for major cities and towns, but also the significant differences outlined above. The new Government will have to draw on the various projects initiated by the previous Government to achieve broadband coverage in a reasonable time.

Because of previous policy decisions, in particular the privatisation of Telstra as a single entity, the ALP Government will have many areas of policy and legislation to resolve before such a network is implemented.

But at least we have started thinking (and talking) about it!

ENDNOTES

1 The website of the ACMA (Australian Communications and Media Authority) shows that Licence No. 240 was issued on 9 Oct 2007 – see www.acma.gov.au/WEB/STANDARD/pc=PC_310408.

2 In the later revisions to the Telecommunications Act 1997, made in association with the *Telecommunications (Consumer Protection and Service Standards) Act 1999*, there has been a requirement placed on Telstra to make available '... a carriage service that provides digital data capability comparable to an ISDN channel' if required, but this is a separate obligation rather than covered by the USO funding scheme.

3 The Inquiry said these concerns relate primarily to: the timely installation, repair and reliability of basic telephone services; mobile phone coverage at affordable prices; and, reliable access to the Internet and data speeds generally.

4 The Senate Environment, Communications, Information Technology and the Arts Committee 2005.

5 The members of the G9 are AAPT, Internode, iiNet, Macquarie Telecom, Optus, Powertel, Primus, Soul and TransACT.

6 The G9 Model is detailed in a paper by Dr Jerome Fahrer (2006) of the Allens Consulting Group.

7 ACCC, '*G9/FANOC FTTN special access undertaking (May 2007)*' available at www.accc.gov.au/content/index.phtml/itemId/788471.

8 The title 'worlds greatest luddite' was 'awarded' to Senator Alston in 2001 by the respected UK IT Newspaper, *The Register.* Available from: www.theregister.co.uk/2001/03/28/this_man_must/.

9 Page Research Centre Ltd, March 2005 '*Future Proofing Telecommunications in Non-Metropolitan Australia*' available at www.page.org.au.

10 Government announcement of 17 August 2005. Available from: www.dcita.gov.au/communications_for_consumers/internet/broadband_for_consumers/australian_government_broadband_initiatives.

11 Senator Coonan, Media Release 18 June 2007 'Australia Connected: Fast affordable broadband for all Australians'. Available from: www.minister.dcita.gov.au/media/media_releases/australia_connected_fast_affordable_broadband_for_all_australians.

12 WiMax is being standardised by the IEEE. The earlier standard, 802.16d or *Fixed WiMax* has been largely replaced by 802.16e or *Mobile WiMax* , as the latter standard is able to provide service to both fixed and mobile users.

13 Recent unconfirmed reports have said that Deutsche Telekom Asia may no longer be interested in involvement.

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Peter was the founding Chair of the Australian Communication Industry Forum Network Reference Panel, developing standards for the interconnection of networks in a multi-network environment. Until his retirement from Telstra in May 2000 he led Telstra's work on technical regulation. Since that time he has worked as Principal of Pondarosa Communications Pty Ltd, on projects for clients including the ACA /ACMA, the ACCC, ACIF, Multimedia Victoria, DCITA and the Productivity Commission. He is a member of the TJA Board of Editors, and works as a Senior Researcher with the Network Insight Institute. He has served as an Adjunct Professor at RMIT University.

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