AI Chatbot Innovation – Leading toward Consumer Satisfaction, Electronic Word of Mouth and Continuous Intention in Online Shopping

Asad Hassan Butt
Department of Marketing, Faculty of Business Administration, University of Tabuk, Tabuk, Saudi Arabia

Hassan Ahmad
Business School, Liaoning University, Shenyang, PR China

Abstract: AI-powered chatbots have emerged as influential tools in the realm of online shopping, effectively driving digital users toward heightened satisfaction, sustained usage intention and positive electronic word of mouth (e-WOM). This research delves deep into the intricate behavioural dynamics that consumers exhibit in their interactions with AI chatbots. A comprehensive online survey, encompassing 554 respondents who willingly engaged with AI chatbots, was conducted, with a focus on established frameworks like the information systems success (ISS) model, the technology acceptance model (TAM), engagement, and the elicitation of pleasurable feelings. The study's findings underscore the pivotal role AI chatbots play in elevating user satisfaction and, in turn, predicting positive outcomes. These insights hold immense value for brand managers, offering a nuanced understanding of Indian online shoppers' behaviour. Furthermore, the study highlights the significant impact of e-WOM generated by AI chatbots within the online shopping domain, further solidifying their role as essential components of digital services in the contemporary landscape. As digital services continue to shape and define modern business operations, AI chatbots have emerged as critical facilitators in enhancing the satisfaction of digital users, making them indispensable for businesses seeking to thrive in the digital realm.

Keywords: AI chatbots, perceived enjoyment, perceived usefulness, ISS model, e-WOM

Introduction

Artificial intelligence (AI) has brought about transformative changes in how organisations operate and engage with their digital era customers (Jeon, 2018; Letheren *et al.*, 2020). One

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significant shift is evident in the realm of service systems, where AI-powered chatbots (Gkinko *et al.*, 2022; Prentice *et al.*, 2020) have revolutionised interactions between customers and businesses. It is essential to distinguish these chatbots from robotic automation processes (RBAs) (Hill *et al.*, 2015; Saboo *et al.*, 2016; Willcocks *et al.*, 2017). While RBAs respond to specific queries, AI chatbots exhibit adaptability, tailoring their responses to meet the ever-evolving needs and desires of customers. Across diverse industries, the implementation of AI chatbots has become a common strategy for catering to end users. These chatbots facilitate human–machine conversations through natural language (Sands *et al.*, 2020; Yu *et al.*, 2022). By harnessing AI tools, businesses can engage consumers and perform various tasks through machine learning (Araujo, 2018; Butt, Ahmad, Goraya *et al.*, 2021). In their roles, chatbots offer rapid responses sought by users and foster robust relationships between users and organisations (Chung *et al.*, 2018; Dwivedi *et al.*, 2021; Lin, 2015). AI conversational chatbots bring substantial value to both organisations and users by providing informative and entertaining interactions (Araujo, 2018; Radziwill *et al.*, 2017; Siala *et al.*, 2022).

Much research is available on the adoption of or intention to use chatbots (Ashfaq *et al.*, 2020; Przegalinska *et al.*, 2019); however, many companies are hesitant to implement such technologies because some consumers do not feel comfortable engaging with machines (Nguyen *et al.*, 2019; Willems *et al.*, 2019). But technology is available to make life more convenient regarding shopping (Butt, Ahmad, Muzaffar *et al.*, 2021; Chung *et al.*, 2018) and other services such as job applications (Collins *et al.*, 2021; van Esch *et al.*, 2020). Hence, it is assumed that AI chatbots will be engaged in the future to provide better services to the end user (Fotheringham *et al.*, 2022; Whitler, 2016; Y. Wang *et al.*, 2021). The research explains that AI chatbots prove helpful in enhancing usefulness and satisfaction (Ashfaq *et al.*, 2020). It is also stated that AI chatbots can engage customer and brand relationships and improve customer satisfaction (Chung *et al.*, 2018; Kubo, 2013). The benefits received after the use of technology helps the user to comprehend the experience involved with it (Fagan *et al.*, 2012; Wang, Butt, Zhang, Shafique *et al.*, 2021). Further, AI chatbots can also predict positive attitudes, satisfaction and intention to use such e-services (Adam *et al.*, 2020; Araújo & Casais, 2020; Xuequn Wang *et al.*, 2022). We understand that, with AI chatbots, the higher the engagement, the higher the consumers' satisfaction levels are. The potential of AI chatbots is limitless as they can perform according to a situation. Hence, organisations can engage human–chatbot interaction while increasing satisfaction and electronic word of mouth (e-WOM).

Studying AI chatbots within the context of Indian consumer behaviour in online shopping is of paramount importance. India's e-commerce sector has experienced exponential growth, making it crucial to understand how AI chatbots impact this expanding market. These virtual

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assistants have the potential to engage customers around the clock, offering personalised recommendations and cost-effective support. The current study focuses on understanding customer engagement using AI chatbots while online shopping. Hence, the study highlights the following research questions (RQs) — RQ1: Will consumers be satisfied with AI chatbots? And RQ2: Will AI chatbots help organisations attain positive e-WOM and continuous intention towards it (CINT)? The RQs addressed here will be answered by the results of this study. The studies on AI chatbots need to further focus on consumers' behavioural aspects and how to help organisations grow. There are many studies on AI chatbots, but more are required to understand the gap between consumer behaviour and AI technology regarding chatbots for online shopping. The satisfaction, CINT and e-WOM effects need to be better understood, and the current study will try to bridge this gap in light of previous knowledgeable studies. The present research framework will highlight the technology acceptance model (TAM), information systems success (ISS), AI chatbot engagement, AI chatbot satisfaction, attitudes, e-WOM, CINT and perceived enjoyment toward using AI chatbots. Large organisations such as WeChat, Amazon, Skype, Facebook, and eBay are already using AI chatbot services to cater to end-users' needs (Luo *et al.*, 2019; Stevens *et al.*, 2020). The future of chatbots is promising because of their functions due to AI tools (Ciechanowski *et al.*, 2019; Gupta *et al.*, 2020; Przegalinska *et al.*, 2019).

Investigating AI chatbots' influence can uncover insights into enhancing customer engagement, tailoring services to diverse cultural preferences, and improving trust and security perceptions in a country where online fraud concerns persist. Furthermore, analysing customer interactions with AI chatbots can provide invaluable feedback, illuminate emerging trends, and bolster competitive advantages in this dynamic and evolving marketplace. As India's online shopping landscape continues to evolve, research on AI chatbots can guide businesses in effectively navigating this promising terrain and to stay attuned to the shifting preferences and behaviours of Indian consumers. In the realm of comprehending CINT with AI chatbots, two robust indicators emerge: satisfaction and attitude (Ashfaq *et al.*, 2020; Butt *et al.*, 2023). Thus, in the pursuit of unravelling the ongoing intent of AI chatbot users and their e-WOM, it becomes imperative to explore their antecedents – satisfaction, attitude and engagement – in the context of the TAM and ISS theories. These theories, when juxtaposed with various AI-related variables, serve as the vital link, addressing the void elucidated in this study. These theories used with other AI aspect variables will also bridge this gap. The provision of superior service fosters brand loyalty, consequently nurturing positive e-WOM and satisfaction (Park & Lee, 2008). Attitude stands as another influential factor, exerting a strong influence on end-users' satisfaction with innovative technologies (Han *et al.*, 2014).

Recent studies have shown that enjoyment is another essential factor in AI tools for satisfaction and CINT (Ashfaq *et al.*, 2020; Pillai *et al.*, 2020; Wang, Butt, Zhang, Ahmad *et al.*, 2021). Thus, the interplay of enjoyment and attitude takes centre stage, illuminating AI chatbot engagement as formidable predictors in shaping CINT and satisfaction within the realm of online shopping. The current study using ISS, TAM and other consumer behaviour aspects will bridge the gap, i.e., the AI relationship with consumer behaviour. The research framework focuses on understanding satisfaction effects on CINT and e-WOM of AI chatbot services in the shopping context. The study will help managers develop better consumer strategies regarding AI chatbots for shopping online. The higher quality of information and services will help consumers' satisfaction increase, which could lead to CINT and e-WOM (Ashfaq *et al.*, 2020; Kim *et al.*, 2018). The following parts of this study include the Literature Review, Methodology, Research Analysis, Discussion and Conclusion.

Research Framework and Hypothesis

AI chatbots – information systems success – (ISS)

The ISS model's information and service quality metrics were proposed by Delone *et al.* (2003). The ISS model predicts customer satisfaction with using technology; so it is vital to understand its information and service quality (DeLone *et al.*, 2016; Freeze *et al.*, 2019). A timely, accurate response to the end-user's needs and wants is considered to be information quality (Chung *et al.*, 2018; Yeoh *et al.*, 2016). Hence, we can predict that the AI chatbot's information quality (AIIQ) is paramount in e-commerce. AIIQ can predict the end-user's behaviour toward the CINT of AI-enabled chatbot services. Consumers require time and information to buy a product online, and the ISS model predicts users' behaviour toward technology usage (Santos, 2011; Yeoh *et al.*, 2010). AIIQ can provide such information accurately and quickly respond to satisfy the end user. It is stated that information quality is a critical component in services because it facilitates better-informed decisions (Adam *et al.*, 2020; Sharma *et al.*, 2019). Precise and relevant information can enhance an AI chatbot user's satisfaction.

The ISS model characterises service quality as the provision of timely responses to enquiries with a focus on individualised attention, thereby enhancing the satisfaction of end users (Kallweit *et al.*, 2014; Williams *et al.*, 2022). It is equally imperative to gain insight into consumer satisfaction and the sustained use of technology (Peng *et al.*, 2022; Setia *et al.*, 2013). AI chatbot service quality (AISQ) can predict consumers' positive behaviour toward satisfaction and its CINT. AISQ can also help organisations develop better end-user services through AI tools. Additionally, an organisation's strong reputation serves as a predictor of superior service, contributing to consumer satisfaction and continued intention (Sung *et al.*,

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2021; Veeramootoo *et al.*, 2018). Robust chatbot platforms designed to cater to consumers' needs and desires emerge as reliable predictors of both satisfaction and CINT. Service systems characterised by rapid responses and user-friendly interfaces play a pivotal role in cultivating trust in an organisation (Gao *et al.*, 2017; Kumar *et al.*, 2016; Leung *et al.*, 2022). Hence, it is reasonable to infer that AISQ holds the potential to assist organisations in crafting engaging human–computer interaction services within the domain of online shopping. We propose the following:

H1a: AIIQ positively influences AI chatbot satisfaction;

H1b: AISQ positively influences AI chatbot satisfaction.

AI chatbot perceived usefulness (PUCB)

The technology acceptance model is well known among academicians and practitioners when discussing new technology. TAM dimensions of perceived ease of use and perceived usefulness (PUCB) are critical predictors in adopting technology services (Koul *et al.*, 2018; Manis *et al.*, 2019; Scherer *et al.*, 2019). The current study focuses on understanding the usefulness of AI chatbots in online shopping. The usefulness of technology is considered a benefit that can enhance the end user's experience (Amin *et al.*, 2014; Kawakami *et al.*, 2013; Tao *et al.*, 2018). PUCB has been used in previous studies as a strong predictor for understanding the satisfaction and CINT of a technology (Kapoor *et al.*, 2014; Manis *et al.*, 2019; Sánchez-Prieto *et al.*, 2017). Further, the dimensions of TAM predict a positive attitude toward the use of technology (J. B. Kim, 2012; Milberg *et al.*, 2021; Olsson *et al.*, 2013). Positive attitudes can also predict strong foundations for satisfaction (Ahmad *et al.*, 2022; Quet *et al.*, 2014; Suh & Youjae, 2006). Hence, PUCB can highlight the positive usage of AI chatbots in an online shopping context that may help organisations develop better strategies. The usefulness of technology can enhance the customer's satisfaction levels, leading to positive e-WOM and CINT. The use of AI chatbots in online shopping may improve such aspects. Figure 1 represents the conceptual framework of this study. It provides an overview of TAM and ISS theory impact on AI chatbot satisfaction. Attitude, enjoyment and engagement of AI chatbots also impact on satisfaction. We further assume that satisfaction of AI chatbots will have a positive impact on e-WOM and CINT to use such AI chatbot services. We propose the following:

H2a: PUCB positively influences attitude toward AI chatbots;

H2b: PUCB of AI chatbots positively influences AI chatbot satisfaction.

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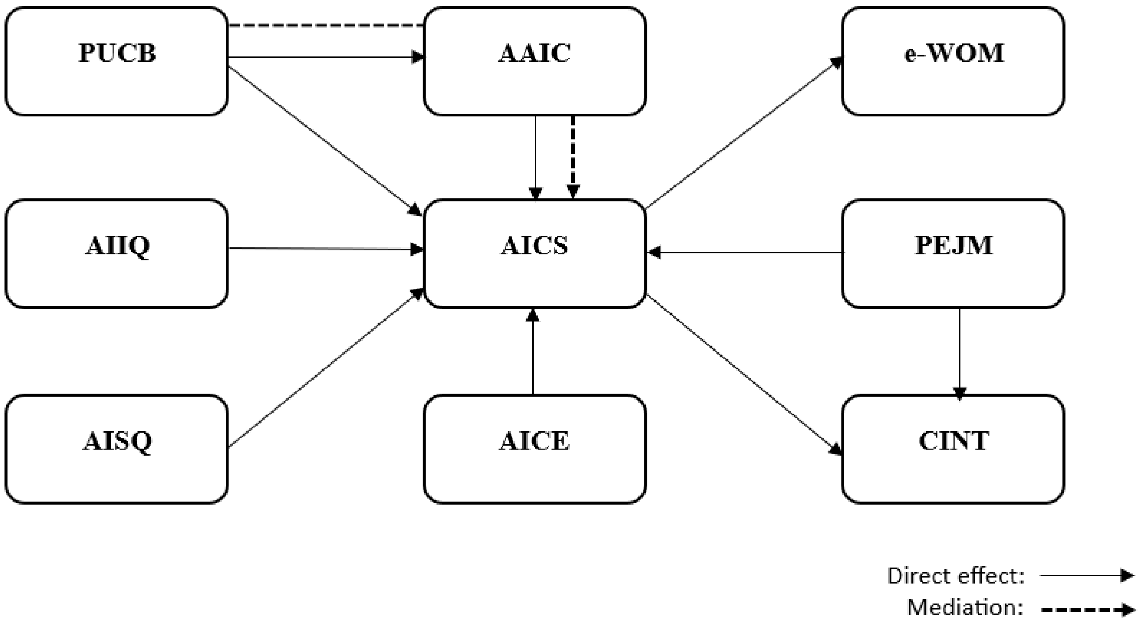

Note: PUCB: Perceived usefulness of AI chatbot, **AIIQ**: AI chatbot information quality, **AISQ**: AI chatbot service quality, **AAIC**: Attitude towards AI chatbots, **AICE**: AI chatbot engagement, **AICS**: AI chatbot satisfaction, **PEJM**: Perceived enjoyment, **e-WOM**: Electronic word of mouth, **CINT**: Continuous intention

Figure 1. Conceptual framework

Attitude toward AI chatbots (AAIC)

Attitude is an individual's belief about a particular product or someone that may be favourable or unfavourable (Ajzen, 1991, 2001; Cheng *et al.*, 2021). A positive attitude can enhance consumers' satisfaction (Chou *et al.*, 2020; Suh & Youjae, 2006; X. Wang, M. J. Haque, *et al.*, 2021). Previous studies have focused on understanding the attitude's effect on satisfaction (Chiu *et al.*, 2021; Kissi *et al.*, 2020; Ye *et al.*, 2017). Hence, attitudes toward AI chatbots (AAIC) can enhance customer satisfaction. AAIC will further provide positive aspects of the behaviour of consumers in the online shopping context. It is further predicted that AAIC will positively mediate PUCB and AI chatbot satisfaction. As we have indicated, attitude positively impacts satisfaction and CINT (Cronin, 2010; Han *et al.*, 2014; Spielmann *et al.*, 2018). We can assume that AAIC will also play a positive role in direct and mediating effects. We propose the following:

H3a: AIIC positively influences AI chatbot satisfaction

H3b: AIIC mediates the relationship between the PUCB and AI chatbot satisfaction

AI chatbot engagement (AICE)

Technology engagement can also enhance consumers' satisfaction (Kang, 2019; Kosiba *et al.*, 2018). Brands are implementing tech-savvy strategies to attract customers. Novel technologies such as AI can impact on consumer satisfaction and loyalty toward the brand

(Barry *et al.*, 2018; Gulati, 2019; Yusuf *et al.*, 2018). The engagement concept helps consumers develop positive beliefs about brand loyalty, awareness and satisfaction (Baker *et al.*, 2010; Jiménez-Barreto *et al.*, 2021; Van Doorn *et al.*, 2010). The use of AI chatbot engagement (AICE) in the current study will help us understand consumer behaviour toward such innovative technologies in online shopping. The engagement involves the customer's cognitive, emotional and behavioural aspects of brand loyalty and satisfaction (Bryce *et al.*, 2015; McLean *et al.*, 2019; Mende *et al.*, 2020). Engaging behaviour can lead to positive outcomes for consumers and the organisation (Tarute *et al.*, 2017). Hence, we can assume from the previous studies that the AICE may play a significant role in understanding the consumer's satisfaction with chatbots while shopping. A consumer's engagement with a brand's services leads to satisfaction and CINT (Du Plessis *et al.*, 2010; Hu *et al.*, 2021; Moriuchi, 2019). Therefore, the current research study of AICE will also provide the same valuable results as previous studies. We propose the following:

H4: AICE positively influences AI chatbot satisfaction.

AI chatbot satisfaction (AICS)

Previous studies have highlighted satisfaction as a strong predictor of CINT (Wu *et al.*, 2016) and e-WOM (Peddibhotla *et al.*, 2007; Suh & Wagner, 2017). Satisfaction for a consumer can include price, usefulness or benefit, time and other factors that can enhance their experience and expertise. Higher satisfaction levels lead to positive CINT toward using a technology (Ashfaq *et al.*, 2020; Asad Hassan Butt *et al.*, 2021; Sabharwal *et al.*, 2015). Hence, AICS will positively impact the CINT of such technology usage in shopping. Another factor that can play a crucial role in understanding consumer behaviour is a brand's positive e-WOM. If satisfaction is high, it may lead to positive e-WOM (Uslu, 2020; Yang, 2017). We argue that the AICS will positively impact consumers' e-WOM and CINT toward such services in the online shopping context. Hence, we propose the following:

H5a: AICS positively influences e-WOM;

H5b: AICS positively influences CINT.

Perceived enjoyment (PEJM)

Another factor that plays a crucial role in understanding consumers' behaviour toward innovative technologies is enjoyment (Kaufmann *et al.*, 2017; McGloin *et al.*, 2016). Perceived enjoyment (PEJM) can positively affect consumers' satisfaction and CINT toward the brand services, such as chatbots (Ashfaq *et al.*, 2020). The literature has established that enjoyment is a strong predictor of understanding consumer behaviour toward chatbot services regarding usage intention (Jang *et al.*, 2019; Xuhui Wang *et al.*, 2020). Using PEJM can enhance consumers' satisfaction and CINT in chatbot services (Chung *et al.*, 2018; Gursoy *et al.*, 2019; M. Park *et al.*, 2020). Other studies have revealed the importance of PEJM when adopting new technologies (Alalwan *et al.*, 2018; Lee *et al.*, 2019). Understandably, human–computer interaction, such as with AI chatbots, helps people to experience fun and enjoyment. Hence, the enjoyment of using a technology while shopping can impact on a consumer's satisfaction and continuous intention (Holdack *et al.*, 2022; Kuo *et al.*, 2017; Tung *et al.*, 2017). Therefore, we propose the following:

H6a: PEJM positively influences AICS;

H6b: PEJM positively influences CINT.

Methodology

A renowned online retailer in India, Flipkart, is featured in this study. Flipkart is an online shopping website with a 31.9% market share, and its rival Amazon is not far behind with a 31.2% market share (Chaudhary, 2019; Chopra, 2019). Flipkart currently has over 200 million registered users (Singh, 2020). In 2018, Flipkart launched its chatbot services on its website and WhatsApp (Das, 2018). The company is still working on AI-enabled chatbots by continuously improving them to then improve customer experience. The company even introduced a haggling chatbot to help the end user negotiate prices with its unique AI machine-learning tools (Das, 2018). Hence, the current study focuses on understanding the AI-enabled chatbot services employed by India's largest e-commerce website. India boasts a vastly sized market with the potential for exponential growth. Furthermore, there has been a notable surge in digital technology adoption, particularly in terms of smartphone usage and internet access. India's cultural diversity contributes to a multifaceted consumer base shaped by various cultural and regional influences. Additionally, it is important to note that the e-commerce sector in India is marked by intense competition.

The study is structured as a survey. Convenience sampling was used to gather the data from the Indian online shopping market. Indian marketing is extensive and will therefore provide useful information about local consumers. The questionnaire was floated online using different social media platforms in India, such as Facebook and WhatsApp. The questionnaire wasn't translated into the Hindi language as the literacy rate is high in India, and the consumers of technology services are aware of such services. Even though the sample participants were mindful of chatbot services, they were informed in the form of an introduction at the start of the questionnaire to provide their user experience with Flipkart's AI chatbot services while shopping. The items for PUCB, AIIQ, AISQ, and AICS were adapted from (Abdullah *et al.*, 2016; Ashfaq *et al.*, 2020). The items for AICE and AAIC were adapted from Moriuchi *et al.* (2020). The items for CINT were taken from Evanschitzky *et al.* (2015). The items for PEJM were taken from Pillai *et al.* (2020).

The total number of questionnaires returned was 581. Out of these, only 554 were recorded for further analysis. Some responses were found to be incomplete or appeared to be duplicated. Therefore, following a thorough screening process, only the responses that met the criteria were considered for inclusion in the Smart Partial Least Squares (PLS) analysis. The response rate was 95%. COVID-19 has completely changed the business environment and consequently organisations focus more on AI tools to provide better services. Hence, studying Flipkart from India allows us to understand the AI-enabled chatbot services while shopping online. The Indian population is enormous, which has led to more technological services being introduced to benefit end users. Therefore, the 554 responses will give us valuable insights into Indian consumers using AI-enabled chatbot services for shopping online. Table 1 represents the demographic profile of the respondents.

Table 1. Respondents' profiles

Features	Distribution	Frequency	%
Gender	Male	351	63.36
	Female	203	36.64
Age	21–25	133	24.01
	26–30	262	47.29
	31–35	117	21.12
	36–40	42	7.58
Education	High school	67	12.09
	Undergraduate degree	177	31.95
	Master's degree	281	50.72
	PhD degree	29	5.23
Occupation	Student	247	44.58
	Job	219	39.53
	Business	88	15.88

Research Data Analysis

Multicollinearity and common method bias

Using a variance inflation factor (VIF) provides a method to evaluate the multicollinearity issues in a model. Multicollinearity indicates the correlation between independent variables, and the existence of multicollinearity may contaminate a study's inferences. VIF values are much lower than the threshold of five, as shown in Table 2; therefore, this study is free from the problem of multicollinearity. Similarly, the common method bias (CMB) or common method variance is also a concern. However, the CMB's multicollinearity issue is related to the methodology, not the constructs or analysis method. We used Bagozzi *et al.* (1988) and Kock (2015) methods to assess the CMB problem. Similarly, another way to detect CMB is to apply Kock's full collinearity test: if the inner VIF value is lower than the five thresholds, the study is free from CMB (Kock, 2015).

Assessment of measurement model

Before testing a study's hypothesis, the researcher must test the reliability and validity of the data. Partial least squares structural equation modelling consists of two measurement models that assess the reliability and validity of data and constructs. The second model also tests a study's hypothesis (Hair *et al.*, 2019). Reliability can be assessed through the factor loadings, Cronbach's alpha average variance, and composite reliability. Cronbach's alpha and composite reliability indicate the internal consistency, factor loadings confirm the indicator reliability and content validity, whereas the average variance extracted is used to assess the convergent validity.

Table 2. Reliability and validity

Variables	Item code	Factor loadings	VIF
Attitude toward AI chatbots	α =0.807, rho_A=0.809, CR=0.886, AVE=0.721		
The use of AI chatbot for shopping is very good.	AAIC1	0.849	1.69
The use of AI chatbot for shopping is a smart decision to make.	AAIC2	0.843	1.795
I have a positive impression of using AI chatbot for shopping.	AAIC3	0.856	1.774
AI chatbot engagement	α =0.857, rho_A=0.857, CR=0.931, AVE=0.779		
The use of AI chatbot grabs my attention while shopping online.	AICE1	0.845	1.817
I felt involved in online shopping while using AI chatbot.	AICE2	0.92	3.01
The interaction with AI chatbot while shopping excited me.	AICE3	0.881	2.474
AI chatbot satisfaction	α =0.856, rho_A=0.865, CR=0.905, AVE=0.706		
I am satisfied with the use of AI chatbot while shopping.	AICS1	0.693	1.375
I am satisfied with the use of AI chatbot functions.	AICS2	0.839	2.199
I am satisfied with the information and service quality of AI chatbot.	AICS3	0.906	3.348
Overall, I am satisfied with the AI chatbot.	AICS4	0.905	3.24
AI chatbot information quality	α =0.852, rho_A=0.853, CR=0.901, AVE=0.695		

Variables	Item code	Factor loadings	VIF
The AI chatbot provides me with clear information while shopping.	AIIQ1	0.827	2.11
The AI chatbot provides the information in a useful format.	AIIQ2	0.859	2.779
I get information on time through this AI chatbot.	AIIQ3	0.892	3.5
The information is sufficient for me through this AI chatbot.	AIIQ4	0.75	1.481
AI chatbot service quality	α =0.845, rho_A=0.849, CR=0.897, AVE=0.685		
The AI chatbot offers an appealing visual display.	AISQ2	0.783	1.87
The interface of AI chatbot gives a modern look.	AISQ3	0.873	2.36
The right solutions for my response were provided by AI chatbot.	AISQ4	0.888	2.661
It gave me a prompt response.	AISQ5	0.761	1.55
Continuous intention	α =0.892, rho_A=0.899, CR=0.933, AVE=0.824		
I strongly recommended others to use AI chatbot service.	CINT1	0.857	2.012
I frequently used the AI chatbot for shopping experience.	CINT2	0.931	3.744
I plan to continue using AI chatbot service in the future.	CINT3	0.933	3.671
Perceived enjoyment	α =0.914, rho_A=0.914, CR=0.939, AVE=0.795		
I enjoyed interacting with AI chatbot.	PEJM1	0.864	2.515
It was a pleasant way to shop with AI chatbot.	PEJM2	0.881	2.61
AI chatbot recommendation was pleasurable during shopping.	PEJM3	0.920	3.741
I was absorbed well in shopping with the use of AI chatbot.	PEJM4	0.899	3.104
Perceived usefulness of AI chatbots	α=0.878, rho_A=0.882, CR=0.925, AVE=0.804		
My effectiveness was enhanced by the use of AI chatbot.	PUCB1	0.891	2.414
My productivity was increased by the use of AI chatbot.	PUCB2	0.932	3.484
It was useful for me to do shopping with the AI chatbot.	PUCB3	0.865	2.281
e-WOM	α=0.898, rho_A=0.901, CR=0.936, AVE=0.831		
I shared my experience of AI chatbot.	e-WOM1	0.907	3.153
I spoke positively about the AI chatbot.	e-WOM2	0.934	3.921

Variables	Item code	Factor loadings	VIF
I have recommended this AI chatbot shopping website to others.	e-WOM3	0.893	2.306

Note: α= Cronbach's alpha; CR= Composite reliability; AVE= Average variance extracted; rho_A= dependability of the composite scale

Discriminant validity

Discriminant validity evaluates how the constructs of studies differ from each other in the context of the same model (Fornell *et al.*, 1982). Fornell-Larcker and HTMT (Heterotrait monotrait) ratios are commonly used to assess the discriminant validity (Fornell *et al.*, 1981). With the Fornell-Larcker criterion, when the square root of AVE is compared with the inter-construct correlation, the AVE's square root must be more significant than the correlation. On the other hand, the HTMT ratio is another measure that uses the correlation between variables based on a Monte Carlo simulation. HTMT ratio must be lower than .85 and AVE's square root must be greater than the correlation values in the same column in the Fornell-Larcker criterion. All the values of the Fornell-Larcker criterion and HTMT ratio reported in Table 3 are according to the standards.

Table 3. Discriminant validity and model fit

	AAIC	AICE	AICS	AIIQ	AISQ	CINT	PEJM	PUCB	e-WOM	GOF	SRMR	NFI
Fornell-Larcker criterion (discriminant validity)												
AAIC	**0.849**											
AICE	0.427	**0.882**										
AICS	0.624	0.693	**0.84**									
AIIQ	0.555	0.652	0.667	**0.834**								
AISQ	0.19	0.512	0.444	0.35	**0.828**							
CINT	0.505	0.586	0.723	0.603	0.46	**0.908**						
PEJM	0.641	0.582	0.698	0.588	0.277	0.534	**0.891**					
PUCB	0.465	0.712	0.728	0.615	0.504	0.65	0.515	**0.896**				
e-WOM	0.435	0.704	0.585	0.557	0.395	0.532	0.551	0.578	**0.911**			
HTMT ratio (discriminant validity)												
AAIC												
AICE	0.511											
AICS	0.745	0.811										
AIIQ	0.668	0.76	0.783									
AISQ	0.223	0.596	0.523	0.411								
CINT	0.594	0.669	0.83	0.692	0.529							
PEJM	0.747	0.657	0.786	0.666	0.313	0.591						
PUCB	0.547	0.822	0.844	0.707	0.578	0.732	0.573					
e-WOM	0.504	0.799	0.661	0.633	0.449	0.591	0.606	0.644				
Model fit										**0.585**	**0.79**	**0.063**

Note: AAIC = Attitude toward AI chatbots; AICE = AI chatbot engagement; AICS = AI chatbot satisfaction; AIIQ = AI chatbots information quality; AISQ = AI chatbots service quality; CINT = Continuous intention; PEJM=

Perceived Enjoyment; PUCB = Perceived usefulness of AI chatbots; e-WOM = e-Word of Mouth. The highlighted values within each construct correspond to the square root of the average variance extracted (AVE).

Additionally, Table 3 includes model fit indicators such as SRMR (standardised root mean square residual), NFI (normed fit index), and GOF (goodness of fit), offering insights into the overall model fit. Furthermore, a supplementary note below the table highlights the significance of the AVE square root in the context of the analysis.

Goodness of fit indices

The hypothesis was tested through structural equation modelling using SmartPLS. The study's model has acceptable model fit criteria; values of the fit indices are reported in Table 3. From the SmartPLS model fit index, we have used two values: SRMR and NFI. The threshold for SRMR is closer to 1 and for NFI the standard value must be below 0.08 (Hair *et al.*, 2019). Both values are according to the standard, indicating a good model fit. In addition to these criteria, the researcher has developed another global fitness index known as the goodness of fit index (GOF) (Tenenhaus *et al.*, 2004). This model's GOF value is 0.585, higher than the threshold of 0.36, confirming this study's global validation (see Table 3).

Hypothesis testing results

The proposed model has excellent and acceptable model fit indices, as reported above. Further, R square values indicate adequate explanatory power; R2 values are 0.217, 0.719, 0.525 and 0.342, respectively, as reported in Table 4. H1a and H1b postulate that AIIQ and AISQ positively affect AICS. As reported in Table 4, AIIQ is positively and significantly related to AICS (β=0.110, $p<0.05$), and AISQ also positively affects AICS (β=0.075, $p<0.05$). Therefore, H1a and H1b are supported. H2a and H2b propose a positive and significant impact of the PUCB on AAIC and AICS. Results shown in Table 4 indicate that these hypotheses have been proved. Hence, H2a and H2b are accepted based on empirical results. The testing for H3a and H3b shows that AAIC directly affects the AICS (β=0.180, $p<0.001$), and AAIC plays a mediating role between PUCB and AICS (β=0.084, $p<0.001$). Therefore, H3a and H3b are robustly accepted on empirical grounds. In H4, we proposed a positive and significant impact of AICE on AICS. Results reported in Table 4 support this hypothesis (β=0.135, $p<0.01$); therefore, H4 was accepted. Further results indicate that AICS has a positive impact on e-WOM (β=0.585, $p<0.001$) and on CINT (β=0.686, $p<0.001$). These relationships were proposed in H5a and H5b; thus, H5a and H5b have been supported. PEJM positively and significantly impacts AICS and CINT, as proposed in H6a and H6b. Results provided support for H6a (β=0.257, $p<0.001$), while H6b was rejected based on empirical results shown in Table 4 (β=0.055, $p>0.10$). The structural model of the data is shown in Figure 2.

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Table 4. Hypothesis tests

Hypothesis	Model variables	Beta coefficient (β)	P values	Decision
H1a	AIIQ → AICS	0.110	0.018	Accepted
H1b	AISQ → AICS	0.075	0.022	Accepted
H2a	PUCB → AAIC	0.465	0.000	Accepted
H2b	PUCB → AICS	0.311	0.000	Accepted
H3a	AAIC → AICS	0.180	0.000	Accepted
H3b	PUCB → AAIC →AICS	0.084	0.000	Accepted
H4	AICE → AICS	0.135	0.004	Accepted
H5a	AICS → e-WOM	0.585	0.000	Accepted
H5b	AICS → CINT	0.686	0.000	Accepted
H6a	PEJM → AICS	0.257	0.000	Accepted
H6b	PEJM → CINT	0.055	0.255	Rejected
Constructs	**R squared**			
AAIC	0.217			
AICS	0.719			
CINT	0.525			
e-WOM	0.342			

Note: AAIC = Attitude toward AI chatbots; AICE = AI chatbot engagement; AICS = AI chatbot satisfaction; AIIQ = AI chatbots information quality; AISQ = AI chatbots service quality; CINT = Continuous intention; PEJM = Perceived Enjoyment; PUCB = Perceived usefulness of AI chatbots; e-WOM = e-Word of Mouth

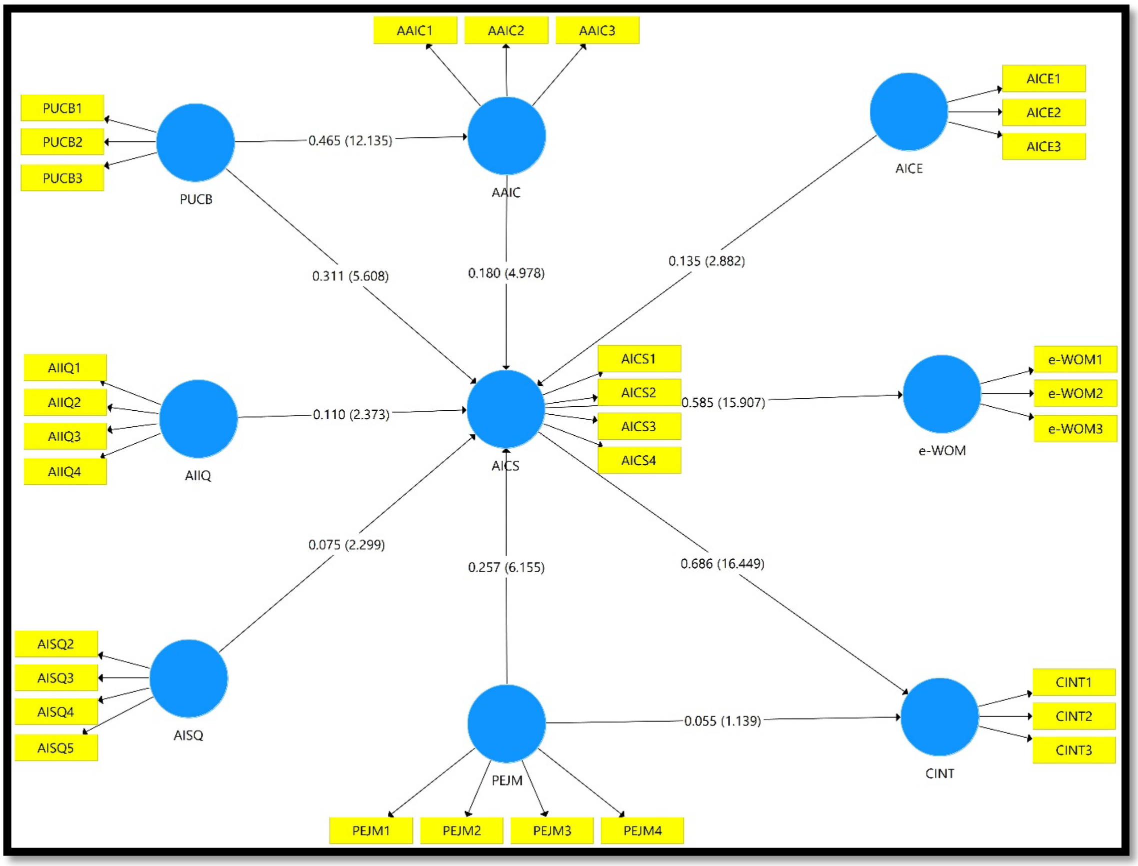

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Figure 2. Structural model

Discussion

AI-powered chatbot services serve a pivotal role in the realm of e-services, impacting both consumers and organisations (Moriuchi *et al.*, 2020; Pantano *et al.*, 2020). The current research framework has yielded promising results with respect to AI chatbot service satisfaction, continued usage intention, and e-WOM promotion. These findings carry significant implications for various theories and behavioural aspects. Evaluating AIIQ and AISQ demonstrates their critical role within the AICS landscape, corroborating prior research (Ashfaq *et al.*, 2020; Sangpikul, 2022). Furthermore, the perceived usefulness, benefits and overall attitude toward AI chatbots during shopping experiences can significantly enhance consumer satisfaction. The findings related to PUCB and AAIC are consistent with previous research studies (Amin *et al.*, 2014; Hess *et al.*, 2014). Moreover, these AI-driven chatbots have demonstrated their potential to enhance consumers' engagement with brand services, yielding positive outcomes. This underscores their role as catalysts for strengthening the bond between consumers and brands.

In our present research, AI chatbot services have demonstrated a remarkable capacity to actively engage consumers, thereby exerting a positive influence on the AICS landscape. This observation aligns harmoniously with prior research endeavours (Gangale *et al.*, 2013; Yusuf *et al.*, 2018), underscoring the consistency of these findings with established trends. Furthermore, our study elucidates the significant impact of AICS on consumers' intention to continue using chatbots (CINT). The results are indicative of consumers' satisfaction with AI chatbot services, as they express eagerness to persist in their usage and enthusiastically spread positive e-WOM about them. This trend aligns cohesively with the research conducted by (Yu *et al.*, 2022; Yusuf *et al.*, 2018). Lastly, our research findings concerning PEJM are in consonance with previous studies. While the data suggests that PEJM may not have a direct positive impact on CINT, it is worth noting that consumers may already be well acquainted with such services. Thus, their satisfaction remains intact, although they may not derive exceptional enjoyment from the experience. It is conceivable that a more extensive sample size could yield nuanced results, shedding further light on this aspect.

Theoretical contributions

The study's findings make significant contributions to the realm of AI chatbot usage theory. Firstly, the results underscore the expansion of the ISS model (Alahmari *et al.*, 2019; Delone *et al.*, 2003) and TAM theory (Manis *et al.*, 2019; Simay *et al.*, 2022) due to the incorporation of AI chatbots. The study's framework was meticulously crafted to illuminate the pivotal determinants of AI chatbots, encompassing user satisfaction, e-WOM propagation, and sustained usage intention. Secondly, the research integrates the notions of positive AICE (Hill *et al.*, 2015) and PEJM (Ashfaq *et al.*, 2020). It extends the literature on the engagement aspect between consumers and organisations, enriching the existing literature concerning the engagement dynamics between consumers and organisations in the context of AI chatbots. Lastly, while numerous studies have explored chatbot adoption across diverse industries, few have delved into the realms of CINT and e-WOM within the sphere of AI-enabled chatbots for shopping. The study's findings serve to illuminate the distinctive role that chatbots equipped with AI tools play in the landscape of online shopping, offering fresh insights into this evolving domain.

The role of attitude is paramount, as it consistently yields positive outcomes, aligning with previous research findings (Sánchez-Prieto *et al.*, 2017; Suh & Youjae, 2006). The framework's results underscore the significance of AI-enabled chatbots in online shopping, as they effectively engage consumers through their utility and enjoyment factors. Consequently, this heightened engagement accelerates the adoption of these services, fostering deeper connections with a brand. As affirmed by earlier studies, consumer engagement holds the potential to enhance brand image and foster loyalty (Helme-Guizon *et al.*, 2019; McLean *et al.*, 2019). Moreover, the study recognises the pivotal role of e-WOM in the digital landscape. It is evident that satisfied consumers interacting with AI chatbots are more likely to contribute positively to e-WOM (Gkinko *et al.*, 2022; Uslu, 2020; Yang, 2017). In summation, the overall findings are distinctly favourable toward AI chatbots, substantially advancing the development of AI theory by shedding light on their pivotal role in enhancing engagement, satisfaction, and e-WOM within the realm of online shopping.

Practical contributions

The study's findings offer valuable insights and practical implications for managers across various domains. First, organisations should prioritise the development of factual information and service systems that ensure the timely delivery of accurate information. This is paramount, as the study predicts that the quality of AI chatbots' information and service delivery significantly influences customer satisfaction. Superior quality in these aspects can play a pivotal role in shaping more effective e-commerce business strategies. In today's COVID-19 environment, the importance of human–machine interaction is further underscored. Therefore, the establishment and enhancement of AIIQ and AISQ are imperative for the successful implementation of AI chatbots in online platforms.

Second, it is essential to acknowledge that innovative technologies like AI chatbots may elicit negative sentiments due to their inability to fully meet the needs and desires of consumers requiring human interaction. Hence, a balanced approach that combines human and machine interaction is recommended. By leveraging AI chatbots alongside human services employees, organisations can provide users with a digitally satisfying experience, fostering continued usage and positive e-WOM.

Third, the study underscores the pivotal role of enjoyment when predicting positive outcomes. Service benefits can be elevated to provide a sense of entertainment or enjoyment while in use. Therefore, retailers should consider incorporating gamification elements that engage consumers and deliver pleasure or joy during their interactions. Lastly, the ease of use and the provision of multiple benefits to end users should be central to the AI chatbots employed by different brands. Simplifying the user experience can have a positive impact on satisfaction, continued usage intention, and e-WOM. Thus, retailers should prioritise the development of user-friendly formats for AI chatbots. It is worth emphasising that AI chatbots distinguish themselves from RBAs by offering greater usefulness, enjoyment and engagement potential. These qualities contribute significantly to enhancing customer satisfaction, continuous usage intention, and positive e-WOM, making AI chatbots a valuable tool for businesses across industries.

Limitations

The study's results are helpful, but they still have limitations. First, the study's respondents were those who have experience using chatbots. For future reference, those respondents who haven't had any experience using AI chatbots could also participate. Technologies exist that are assisted or integrated with AI, such as augmented reality or virtual reality. These can also be used for future research. Second, ISS and TAM theories are well known, but some theories and variables can be incorporated for future studies, such as innovation diffusion theory, AI novelty, AI self-efficacy and technology anxiety. Further, perceived risk and trust can also play a significant part in future studies. Using different theories can provide a different perspective. Consumer culture theory can also perhaps be part of this future direction. Third, the sample comprised 554 respondents, which is good enough to highlight positive results in the framework. However, the Indian population is extensive, so a higher sample size would help to further understand AI chatbots in online shopping. Fourth, a comparative study can also play a key role in understanding AI-enabled chatbots. And last, combining front-line employees and AI chatbots within the real physical environment could be part of the future research.

Future directions

This study's insights offer valuable information for brand managers, enabling them to formulate comprehensive strategies for both online and offline platforms. In the rapidly evolving landscape of brand management, emerging technologies have a pivotal role. These technologies not only serve as effective customer attractors but also play a significant role in elevating the level of engagement between consumers and brands, fostering positive relationships. The integration of AI into brand operations presents a promising avenue in creating an amazing experience for the consumers. AI-driven systems have the capacity to assist consumers, tailoring recommendations based on their moods, attitudes and behaviours. This personalised approach not only enhances the consumer experience but also strengthens the bond between consumers and brands. Furthermore, brand managers can play a crucial role in enhancing employee engagement by providing training on the utilisation of AI. Empowering frontline employees to integrate AI into their sales processes can yield substantial benefits for both the company and its consumers. This synergy between human and AI-driven selling behaviours have the potential to optimise operations and further enhance the overall customer experience. In essence, the strategic incorporation of AI into brand management can lead to a win-win scenario, benefitting the company and its valued consumers.

Conclusion

The current human–machine interaction study was developed to understand consumers' satisfaction, CINT and e-WOM regarding AI chatbots. The use of such technologies is increasing, and many organisations are keen to further develop these services. The results' significance shows that consumers are willing to use these services and spread positive e-WOM. ISS and TAM have demonstrated that consumers find AI chatbots valuable and sound. The use of AI chatbots during online shopping can create immersive engagements for consumers, providing satisfaction, positive attitude and enjoyment. The results show that consumers are willing to develop a positive attitude toward using AI chatbots. Further, the brands or retailers could develop better strategies by introducing human services employees and AI chatbot integration to improve their services. Brands should integrate AI technology within online and offline environments to attract a customer base. AI chatbots can be of assistance not only to consumers but also to frontline employees. Therefore, it can be beneficial for companies to initiate integration of this technology to enhance both employee performance and consumer engagement.

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