THAMMASAT REVIEW
ONLINE ISSN: 2630-0303

Volume 28 No 1 (January-June) 2025 [Page 152-178]

Understanding AI Chatbot Utilization in Vietnam: An Extended Elaboration Likelihood Model Perspective

Xuan Cu Le [a,] *, Tran Hung Nguyen [a] and Thi Thuy Linh Vu [b]

[a] *Department of Economic Information System & Electronic Commerce, Thuongmai University, Vietnam*

[b] *Department of Research Methodology, Thuongmai University, Vietnam*

Received 27 November 2024; Received in revised form 24 March 2025
Accepted 17 April 2025; Available online 25 May 2025

Abstract

Artificial intelligence (AI) chatbots have become an innovative interaction channel between firms and customers in e-commerce. This article aims to explore the essential factors that trigger the intention to use AI chatbots among Vietnamese customers. A research model was demarcated based on the incorporation of user perceptions (i.e., trust and information usefulness) and salient AI chatbot characteristics (i.e., perceived intelligence) into the widely acknowledged *elaboration likelihood model* (ELM). Data was accumulated from 307 respondents who had experienced online purchases and were inclined to use AI chatbots to search for product-related information in online purchases. Structural equation modeling (SEM) was utilized to test proposed hypotheses and validate the research model. Our investigations demonstrated that the central route (i.e., information accuracy and information relevance), peripheral route (i.e., information credibility), and perceived intelligence are the primary motivators of customers' trust and information usefulness toward AI chatbots. Moreover, trust, information usefulness, and perceived intelligence significantly drove usage intention toward AI chatbots. This work developed an insightful research model of usage behavior toward AI chatbots, whereas the interpretation of information-related factors and innate AI chatbot intelligence influencing customer usage in an emerging market had been inadequate. Lastly, the theoretical and practical implications of the model are suggested, which may tempt customers' adoption behavior toward AI chatbots in Vietnam.

Keywords

Artificial intelligence chatbots, Elaboration likelihood model, Perceived intelligence, Trust, Vietnam

*** Corresponding author**: cu.lx@tmu.edu.vn **DOI**: 10.14456/tureview.2025.7

Introduction

Digital technologies have substantially enhanced business performance and firm−customer reciprocity (Cheng & Jiang, 2022). The widespread adoption of Artificial intelligence (AI) chatbots illustrate an accelerating trend of applying digital technologies to improve firms' communication strategies (Nguyen & Le, 2025). These chatbots have increasingly supplanted humans due to operational availability (24/7), error reduction, and cost-effectiveness. AI chatbots are software applications that allow customers to make online conversations with digital devices using natural human language, thereby effectively replacing human-to-human interaction (Nguyen & Le, 2025). AI chatbots have been utilized across various sectors, such as tourism and hospitality (Pillai & Sivathanu, 2020), banking (Eren, 2021), hotels (Nguyen, Phong, & Chi, 2023), and retailing (Chen, Le, & Florence, 2021). Unsurprisingly, the global revenue from AI chatbots reached USD 40.9 million in 2018, with projections suggesting an increase to USD 455.8 million by 2027 (Statista, 2022). The retail sector market size in Vietnam reached USD 207.5 billion from January to October 2024 and is projected to reach USD 350 billion by 2025 (VietnamPlus, 2025). In the era of digital transformation, retailers have attempted to implement business strategies and diversify communication channels using digital technologies, such as AI chatbots, to foster customer experience, customer−retailer relationship, and improve business performance (Le, 2023). However, in the early stage of AI chatbot development, Vietnamese customers may hesitate to experience AI chatbots based on some potential concerns about immature technologies, insufficient information, and perceived risks (Silva et al., 2023). Hence, retailers must understand customers' desires, solve their issues, and trigger their usage of AI chatbots.

AI chatbots are integrated into various platforms, such as websites, mobile applications, and social media (Nguyen & Le, 2025). AI chatbots offer several distinct advantages in terms of convenience, flexibility, accessibility, and real-time interactivity (Cheng & Jiang, 2022). Moreover, AI chatbots can perform tasks typically handled by staff, such as promotion and consultation, and even address issues beyond human capabilities. Consequently, firms willingly adopt AI chatbots as an effective apparatus to support online business (Ruan & Mezei, 2022).

From an academic perspective, AI chatbots in e-commerce have garnered attention from scholars. Multiple theories have been employed to explain and evaluate the importance of AI chatbots in customer perceptions, evaluation, and emotional and behavioral responses. Chen et al. (2021) created a research model of customer satisfaction with AI chatbots in e-commerce across the United States, Canada, South Africa, and India based on the universal technology acceptance model (TAM). Jain and

Gandhi (2021) examined Indian customers' purchase intention through the lens of information and the technological value of AI chatbots. Cheng and Jiang (2022) emphasized that interaction, accessibility, and information value are critical motivations for online purchases using AI chatbots in American e-commerce firms. Le (2023) combined the TAM with the elaboration likelihood model (ELM) to provide an explanation for the use of AI chatbots in retailing. These investigations suggested that information-related characteristics (information quality, persuasiveness, and information credibility), AI chatbot-related characteristics (relative advantage, interactivity, and perceived intelligence), and TAM-related factors (perceived usefulness and AI attitude) play a vital role in promoting AI chatbot adoption and purchase intention. Silva et al. (2023) created a behavioral intention model of AI chatbots in e-retailing to explain how to trigger AI chatbot usage intention using the extensive, unified theory of acceptance and use of technology (UTAUT) and concluded that *performance expectancy* and *trust* significantly predict perceived risk, flow, and behavioral intention toward shopping chatbots. Furthermore, the importance of the formation of trust and behavioral intention was emphasized by Mostafa and Kasamani (2022), who concluded that AI chatbot-related dimensions (compatibility, ease of use, and social influence) are the determinants of initial chatbot trust, which in turn boosts usage intention and customer engagement based on UTAUT, TAM, and diffusion of innovation (DOI) theory.

Mechanisms of customer behaviors toward AI chatbots in retailing have also been explored in developed countries (Chen et al., 2021; Silva et al., 2023). Researchers in Vietnam have paid attention to the impact of AI chatbots on customer behavior in different settings of technology and education (Nguyen et al., 2021), banking (Dung, Chiu, & Le, 2021), hotel industry (Nguyen et al., 2023), and retailing (Le, 2023). Nguyen et al. (2023) increased understanding of customer trust toward AI chatbots through a study of the significant influence of customization and interaction. Le (2023) examined AI chatbot adoption and purchase intention based on TAM and found that perceived usefulness and attitude toward AI facilitate customers' AI chatbot usage intention and purchase behavior. However, the interpretation of information value-related dimensions and the perception of the intelligence of chatbots, which may influence customers' usage intention toward AI chatbots is inadequate. Thus, it is imperative to examine further some key factors that drive customers' intention to use AI chatbots to accumulate product-related information and address customer concerns. This understanding may help us recognize the role of AI chatbots in customers' purchase decisions in an emerging market.

This study's purpose is to explicate customers' intention to use AI chatbots, by focusing on the role of "information value" and AI chatbot characteristics. Information value refers to customers' perceptions of the value of information through AI chatbots (Le, 2023). To achieve this, our study uses the Elaboration Likelihood Model (ELM) to analyze informational value-related factors and their impact on trust and information usefulness. Additionally, the study builds on the ELM by combining the inherent characteristic of AI chatbots (i.e., perceived intelligence) and trust, as recommended by previous research (Cheng & Jiang, 2022; Mostafa & Kasamani, 2022; Pillai & Sivathanu, 2020). Thus, the study provides a significant theoretical contribution by examining and evaluating the usefulness of the research framework of customer usage behavior toward AI chatbots in a developing country such as Vietnam. It also provides practical insights to assist firms and technology developers to strengthen the firm−customer relationship and foster post-adoption behaviors, such as online purchases, by identifying several vital factors of "information value" and perceived intelligence in AI chatbots.

Theoretical Background and Research Model

Elaboration Likelihood Model (ELM)

Elaboration Likelihood Model (ELM), developed by Petty, Cacioppo, and Goldman (1981), was established to explain individuals' usage behavior toward information systems (ISs) based on a comprehensive evaluation process. This model suggests that the extent of evaluation and scrutiny is influenced by both motivations and the ability to process the information. When individuals are highly motivated and capable of thoroughly processing information, they are likely to make well-informed decisions and exhibit effective behaviors. Conversely, if motivation and information processing are diminished, the ability to evaluate and consider information thoroughly may also be compromised.

ELM distinguishes between two motivation and information processing routes: peripheral and central. With the peripheral route, users concentrate on information cues such as information quantity, information expertise, information credibility, the number of users, and reputation (Le, 2023). Individuals take a peripheral route when they are less motivated or incapable of considering information (Petty et al., 1981). Hence, individuals make fewer cognitive efforts and adopt behavioral intentions due to peripheral signals (Filieri, Chen, & Lal Dey, 2017). Thomas, Wirtz, and Weyerer (2019) proposed a customer purchase intention model based on the extended ELM and showed that peripheral cues (review consistency, review expertise, product rating, and website reputation) and central cues (accuracy, completeness, and timeliness) promote review credibility, which in turn motivates customers' purchase decision due to online views. Furthermore, ELM argues that individuals with high-involvement products and/or services are more likely to utilize the central route for information processing, focusing on argument quality (Petty et al., 1981). Central route emphasizes a detailed review and evaluation of information's relevance, accuracy, and completeness before making a decision or performing a behavior. Chen, Yin, and Gong (2023) created a research model based on the theoretical support of ELM to reveal the influence of central cues (reliability and accuracy) and peripheral cues (human-like empathy and recommendation choice) on customers' adoption of AI chatbot recommendations. Roy, Paul, Tiwari, & Mookherjee (2024) showed that ELM dimensions, including perceived information, perceived persuasion, electronic word of mouth (eWOM) credibility, and eWOM usefulness, play an essential role in boosting eWOM adoption and purchase intention. Huo, Zhang, and Ma (2018) revealed that central route-related (accuracy, relevance, and completeness) and source credibility, directly and indirectly, influence trust and health knowledge adoption in light of ELM. Ruan and Mezei (2022) observed that information quality-related dimensions (relevance, accuracy, completeness, credibility, and timeliness) provided by AI chatbot agents are essential determinants of customer satisfaction with these chatbot agents in online purchase assistance.

ELM has been empirically applied in manifold contexts, such as preventative behavior in the COVID-19 pandemic (Cu, 2021), online reviews and shopping (Thomas et al., 2019), eWOM and purchase (Roy, Paul, Tiwari, & Mookherjee, 2024), and online purchase in live-streaming (Yen et al., 2024). Based on the approach of these previous studies, the ELM is applied by this study to examine Vietnamese customers' usage intention toward AI chatbots. The study examines two motivations: the central route (i.e., accuracy and relevance) and peripheral route (i.e., credibility) of AI chatbots' information and their impact on trust and information usefulness. Additionally, we consider "perceived intelligence" as a critical characteristic of AI chatbots because it suggests faith in the ability of AI chatbots to understand and promptly respond to customer requests, impart available product-related information, make conversations, and resolve their issues using natural language (Le, 2023). Pillai and Sivathanu (2020) emphasized the pivotal role of perceived intelligence in boosting AI chatbot adoption intention and actual usage for travel planning. Cheng et al. (2024) indicated that perceived intelligence directly and indirectly influences perceived usefulness, satisfaction, and usage intention toward financial AI services. Other scholars have found that perceived intelligence and trust are crucial in fostering customer intention to adopt AI chatbots (Moussawi, Koufaris, & Benbunan-Fich, 2021; Nyagadza et al., 2022). Cheng and Jiang (2022) emphasized that information value (i.e., accuracy and credibility) and competence (i.e., perceived intelligence) are essential AI chatbot components along with customer trust that significantly cements the firm−customer relationship and customer behavioral responses (i.e., purchase intention and loyalty). Park et al. (2024) asserted that AI chatbots are essential in product knowledge (i.e., information accuracy, perceived intelligence, and trust) and found that product knowledge leads to customers' recognition of usefulness and customer satisfaction with these chatbots. Likewise, Nguyen and Le (2025) demonstrated an underlying mechanism of continuance intention toward banking AI chatbots and investigated the impact of content quality and competence on extrinsic and intrinsic values and satisfaction with these chatbots. Therefore, this study endeavors to examine the influence of information value and perceived intelligence on trust, information usefulness, and usage intention toward AI chatbots in the light of extensive ELM.

Hypotheses Development and Research Model

Accuracy delineates the correctness in mapping information to the appropriate state in the real world that the information represents (Nelson, Todd, & Wixom, 2005). It is a crucial characteristic of the central route in ELM. It significantly influences customer behavior, as it serves as a critical motivation for evaluating products and/or services, thereby fostering trust (Filieri et al., 2017). Information accuracy relies on customers' perception that information is accurate, correct, believable, and credible (Le, 2023; Nguyen & Le, 2021; Thomas et al., 2019). Huo et al. (2018) showed that customers' trust in health knowledge in social media is determined by information quality, including information accuracy, relevance, and completeness. Customers who perceive information as accurate and realistic are more likely to increase trust in social media-based health knowledge. Moreover, researchers confirmed that information accuracy is a key determinant of information usefulness (Park, 2020). Shang, Zhou, and Zuo (2021) suggested a significant relationship between accuracy and information usefulness in social media-based information sharing. Xing and Jiang (2024) argued that information accuracy strongly impacts customer experience, which results in usefulness and customer satisfaction with AI chatbots. Building on these findings, this study will examine the effect of information accuracy on trust and AI chatbots' information usefulness. An increase in customers' perception of information accuracy provided by AI chatbots will result in an improvement in trust and information usefulness from AI chatbots. Consequently, AI chatbots help organizations reduce operation costs in customer care service and enhance service quality. Therefore, the substantial literature demonstrating this leads us to propose the following hypotheses:

H1a: Information accuracy positively affects customer trust in AI chatbots.

H1b: Information accuracy positively affects information usefulness.

Information relevance depicts the extent to which product-related information is applicable and helpful in making distinctions between the competing objects in customers' needs (Sarkar & Sarkar, 2019). This factor indicates information value by reflecting the content firms aim to communicate to customers. Before making decisions or adopting certain behaviors, customers assess products and/or services based on information availability. If the information satisfies customer needs, they will likely evaluate it positively, fostering trust in creators and conveyors. Moreover, customers also consider information relevant to their decision-making process and purchase decisions. Nguyen and Le (2021) investigated the role of information relevance in facilitating customers' trust in information sources in social media to safeguard individuals during the COVID-19 pandemic. Similarly, the positive relationship between information relevance and trust was investigated in health information adoption (Huo et al., 2018), e-government services (Al-Omairi et al., 2021), and banking chatbots (Dung et al., 2021). Additionally, information relevance acts as a catalyst for information usefulness. Park (2020) highlighted that information relevance significantly impacts information usefulness, influencing information acceptance and loyalty in eWOM. Although the influence of information relevance on trust and information usefulness was demonstrated in various online communication contexts (Shang et al., 2021; Zhu, Chang, & Luo, 2016), it has not been empirically tested in AI chatbots. A chatbot is a computer program powered by artificial intelligence capable of interacting with customers in convincing language with natural, sentimental statements. This capability allows AI chatbots to understand customer needs and address concerns (such as product-related information, processes, and operations). Customers will perceive information as relevant, helpful, and important, which may enhance trust, information value, and AI chatbot usage for purchase decisions. These empirical observations lead us to propose the following hypotheses:

H2a: Information relevance positively affects customer trust in AI chatbots.

H2b: Information relevance positively affects information usefulness.

Information credibility reflects customers' assessment of the reliability of information sources related to products and/or services (Cu, 2021). Information is generated by various content creators, including individuals (such as social media users, celebrities, and experts) and organizations (such as firms and governments). Research confirmed that information credibility is a crucial determinant of customers' trust in content creators and information usefulness, leading to certain types of customer behavior. Scholars demonstrated the importance of information credibility in enhancing trust in health knowledge in social media (Dung et al., 2021; Huo et al., 2018). Shang et al. (2021) demonstrated that information credibility significantly impacts healthcare information usefulness, which, in turn, promotes information-sharing behavior on social networks. Park (2020) explored the importance of trustworthiness in evaluating the perceived usefulness of information disseminated through eWOM. Therefore, customers will likely increase their trust in AI chatbots and perceive them as highly useful for information provision. Based on this empirical evidence, the following hypotheses are proposed:

H3a: Information credibility positively affects customer trust in AI chatbots.

H3b: Information credibility positively affects information usefulness.

Trust delineates customers' reasonable expectation that providers possess the characteristics of trustworthiness, which, in turn, stimulates their behavior (Ajzen & Driver, 1991). It offers confidence and guarantees for customers in the safety of using ISs (Awad & Ragowsky, 2008; Rotchanakitumnuai & Speece, 2023). Past studies revealed trust significantly drives customers' adoption behaviors in different ISs. Zhou (2016) demonstrated that trust positively impacts young customers' intentions to adopt ISs. Similarly, Le (2025b) confirmed a significant relationship between trust and the willingness to use mobile banking among older Vietnamese consumers. Likewise, trust captures a vital role in the use intention toward mobile advertising, leading to the strengthening of a long-term firm−customer relationship (Cu & Wang, 2020). Generally, customers are more likely to adopt ISs when they perceive ISs as trustworthy and have confidence in providers. In the research context, if AI chatbots provide information quickly and effectively and address customer concerns, customers will express their trust in AI chatbots, subsequently determining customers' usage toward AI chatbots. Indeed, scholars argued a close relationship between trust and usage intention toward AI chatbots in online purchase (Mostafa & Kasamani, 2022), hospitality and tourism (Pillai & Sivathanu, 2020), and e-retailing (Silva et al., 2023). Consistent with the abovementioned findings (Moussawi et al., 2021), trust is assumed to drive customers' intention to adopt AI chatbots in online purchases. Therefore, these arguments underpin the proposal of the following hypothesis:

H4: Trust positively affects usage intention toward AI chatbots.

Perceived usefulness reflects how customers believe using a particular IS will enhance their performance and help them achieve goals (Sussman & Siegal, 2003). It influences the subjective likelihood that users will seek to improve their performance by adopting ISs. “Information usefulness” means that customers think information adoption can enhance their performance (Park, 2020). In this study, information usefulness is defined as the extent to which AI chatbots help customers absorb more product-related information, resolve issues, and make proper purchase decisions. Consequently, information usefulness is expected to influence customers' acceptance of AI chatbots positively. Park (2020) found that the value of eWOM-based information leads to customers' adoption of eWOM information and their loyalty to social media. Furthermore, perceived usefulness was investigated to predict usage intention toward mobile banking (Le, 2025b) and artificial intelligence (Chatterjee & Sreenivasulu, 2023). Based on this evidence, the study proposes the following hypothesis:

H5: Information usefulness positively affects usage intention toward AI chatbots.

Perceived intelligence reflects the ability of AI chatbots to respond immediately to customers’ requirements in various environmental conditions (Le, 2023). AI chatbots can identify customers’ problems adequately, reducing their difficulties during the conversation (Cheng et al., 2024). Researchers illustrated that AI chatbots have the abilities of competence, intelligence, knowledge, and purpose (Moussawi et al., 2021). The intelligence of AI chatbots is reflected in their ability to communicate efficiently (quickly respond, identify contexts, minimize operational errors, adapt to processes, and remain unaffected by mood), enhance productivity (solve problems, offer suggestions, free up employee time), provide assistance anytime and anywhere, and initiate convenient communication methods (Chen et al., 2021; Le, 2023). Hence, perceived intelligence is closely related to the information usefulness of AI chatbots because these chatbots help customers make purchases and conduct business transactions effectively (Cheng et al., 2024).

In addition, when AI chatbots respond to customers’ questions promptly and assist them with tracking orders, processing payments, and making conversations, users will judge AI chatbots as competent, increasing trust and provoking their willingness to accept these chatbots. Moussawi et al. (2021) substantiated the strong influence of perceived intelligence on perceived usefulness and adoption intention toward personal intelligent agents. Others demonstrated a significant relationship between perceived intelligence, intention to use artificial intelligence (Pillai & Sivathanu, 2020), and AI chatbots for customer purchase (Le, 2023). From these previous findings, the following hypotheses are proposed:

H6: Perceived intelligence positively affects information usefulness.

H7: Perceived intelligence positively affects trust.

H8: Perceived intelligence positively affects usage intention toward AI chatbots.

As depicted in Figure 1, a postulated model is graphically schematized.

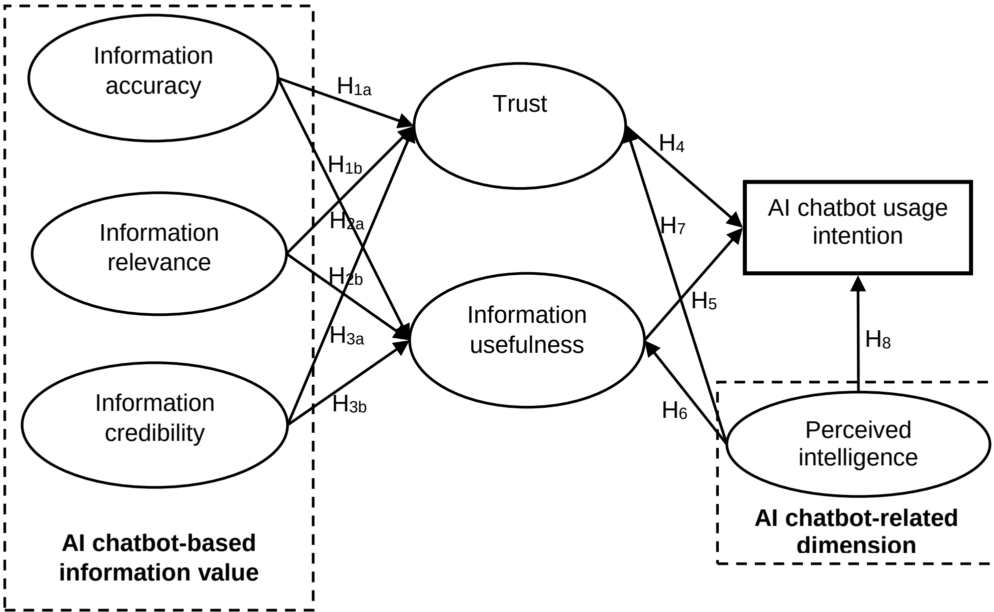

Figure 1 Hypothetical model.

Source: Authors' own work

Research Methodology

Measurement

Measurement scales for the constructs were adapted from previous studies to fit the current AI chatbot context in Vietnam (Cheng et al., 2024; Cheng & Jiang, 2022; Eren, 2021; Le, 2023; Mostafa & Kasamani, 2022; Silva et al., 2023). Discussion and literature review were conducted with seven researchers in the field of Information System (IS) management and e-commerce, as well as five experts in marketing, to identify problems and refine the measurement scales of the research model. The format and content validity were carefully scrutinized, leading to minor modifications of constructs' items, including information relevance, information credibility, and perceived intelligence. Next, a pilot test was conducted with 48 respondents. The results indicated that Cronbach's alpha coefficients (α) for all the constructs exceeded the 0.7 benchmark, ranging from 0.88 (perceived intelligence) to 0.945 (information accuracy) (Hair et al., 2018). Thus, this survey was deemed suitable for further data collection.

A 5-point Likert scale is used for each question, ranging from 1 - strongly disagree to 5 - strongly agree. The scale for information accuracy (four items) was adopted from Filieri et al. (2017); information relevance (four items) was based on Sarkar and Sarkar (2019); and information credibility (three items) follows Luo et al. (2013). Similarly, the scale for trust (three items) was adapted from Awad and Ragowsky (2008); information usefulness (three items) from Sussman and Siegal (2003) and Park (2020); and perceived intelligence (three items) from Bartneck et al. (2009) and Le (2023). Finally, the scale for usage intention toward AI chatbots (three items) was applied and adapted from Davis (1989) and Le (2023). The items used to measure seven constructs are shown in Table 2.

Data Collection

A web-based survey was designed to gather data using Google Forms. This technique has been widely accepted in empirical studies on online customer behavior (Le, 2023; Le, 2025a). The survey encompassed two main parts: (1) four close-ended questions about respondents' socio-demographic profile and (2) items of all the constructs of ELM (including information accuracy, information relevance, information credibility, and information usefulness), trust, perceived intelligence, and AI chatbot usage intention. Based on the national language, the English questionnaire was translated into a Vietnamese questionnaire with the assistance of two Vietnamese language experts. Then, another expert interpreted the Vietnamese version back into English to maintain consistency.

The study employed a convenience sampling method due to its benefits, including cost-effectiveness, time efficiency, and widespread application in empirical IS research (Nguyen & Le, 2021). Participants have experienced online purchases and tend to utilize AI chatbots in online shopping, including students and employees with full-time and part-time jobs. Participants are typically equipped with knowledge and skills regarding digital technologies and are inclined to search product-related information for online purchases via AI chatbots (Le, 2023). Before filling in the questionnaire, we provided the participants with the research purpose, a short introduction, and a video of AI chatbots in online purchases. The questionnaire's introduction emphasized the anonymity, privacy protection, and confidentiality of participants' responses. The video was non-offensive and understandable, allowing the participants to understand AI chatbots and their utilization for online purchases. The survey link was disseminated through a social media platform (i.e., *Facebook*). A total of 342 questionnaires were obtained from June 2022 to August 2022. Responses for each question were thoroughly scrutinized. Thirty-five inadequate questionnaires were discarded due to missing answers and data similarity. Consequently, 307 questionnaires (validity rate of 89.77%) were deemed valid.

The sample characteristics are presented in Table 1. 35.5% of males and 64.5% of females participated in the online survey. Most respondents (78.5%) had gained a college or university education, followed by 21.5% with a postgraduate education. Most participants (80.13%) were between 18 and 29 years old. 49.51% were students, 25.73% had full-time jobs, 19.87% were employed part-time, and 4.89% were unemployed. Among the respondents, students are well-versed in information technology and have acquired familiarity and experience with emerging digital technologies like AI chatbots. They frequently use smart devices and the Internet to search for information and purchase online (Le, 2023).

Table 1 Respondents' description

Variable	**Frequency**	**Percent**
Gender		
Male	109	35.5
Female	198	64.5
Age		
18−24	150	48.86
25−29	96	31.27
≥ 30	61	19.87
Education		
College/university	241	78.5
Postgraduate	66	21.5
Occupation		
Student	152	49.51
Full-time job	79	25.73
Unemployed	15	4.89

Source: Authors' own work

Results

A two-stage analysis approach was conducted to test the hypotheses of the proposed research model (Anderson & Gerbing, 1988). First, to evaluate the measurement, the study measured the scale's reliability and validity (i.e., discriminant and convergent validity) and goodness-of-fit. Second, this study tested the research model using Structural Equation Modeling (SEM). SEM is a well-acknowledged technique in marketing and management (Hair et al., 2018). It is a proper statistical method for explaining marketing phenomena rather than predicting outcome variables (Steenkamp & Baumgartner, 2000). The data were analyzed by using covariance-based structural equation modeling (CB-SEM). In this study, CB-SEM is beneficial as the attention was paid more to theory testing and affirmation than to prediction and theory development (Hair et al., 2018). CB-SEM allows us to validate the theory of ELM, which is an essential step to extend the research framework.

Empirical studies can encounter the issue of common method bias (CMB) when all constructs are measured with the same respondents at the same time. A statistical step using the Harman single factor (HSF) method should be conducted to assess CMB on single respondents in the survey. Seven constructs were loaded into a single factor. The result showed that the HSF value with the principal axis factor is 40.314% of the explained variance, which is lower than the 50% threshold (Podsakoff et al., 2003). Consequently, CMB was unlikely to be an issue in the data set.

Reliability Result

The study analyzed exploratory factor analysis (EFA) with 23 variables to test KMO and Bartlett's test with Promax rotation to confirm the variables' suitability before performing confirmatory factor analysis (CFA). The results showed KMO = 0.934 (>0.05), Sig = 0.000, and the total variance extracted reached 71.448%.

To evaluate the reliability, the study recruited Cronbach's Alpha coefficient (α). Hair et al. (2018) recommended that the α value should be greater than 0.6. The results showed that the α value of 7 constructs fulfills the benchmark value, ranging from 0.909 to 0.933, therefore presenting good reliability (see Table 3).

Convergent Validity and Discriminant Validity

In the confirmatory factor analysis (CFA), composite reliability (CR) and average variance extracted (AVE) are the criteria used to test convergent validity. Hair et al. (2018) stated that CR and AVE should be ≥ 0.7 and ≥ 0.5, respectively. As illustrated in Table 3, the results showed that CR values (between 0.858 and 0.939) and AVE values (between 0.669 and 0.821) satisfy the threshold criteria. Further, standardized loadings ranged from 0.811 to 0.939, which met the cut-off value 0.6 (Chin, Gopal, & Salisbury, 1997). Thus, the study surpassed the convergent validity.

In the confirmatory factor analysis (CFA), composite reliability (CR) and average variance extracted (AVE) are the criteria used to test convergent validity. Hair et al. (2018) stated that CR and AVE should be ≥ 0.7 and ≥ 0.5, respectively. As illustrated in Table 3, the results showed that CR values (between 0.858 and 0.939) and AVE values (between 0.669 and 0.821) satisfy the threshold criteria. Further, standardized loadings ranged from 0.811 to 0.939, which met the cut-off value 0.6 (Chin, Gopal, & Salisbury, 1997). Thus, the study surpassed the convergent validity.

Table 2 Measurement model results

Items	Observation variables	Loadings
Information accuracy (Filieri et al., 2017)		
ACC1	Information via AI chatbots is accurate	0.89
ACC2	Information via AI chatbots is correct	0.923
ACC3	Information via AI chatbots is precisely formulated	0.905
ACC4	Information via AI chatbots is thoroughly written	0.811
Information relevance (Sarkar & Sarkar, 2019)		
REL1	AI chatbots meet my needs (e.g., searching and shopping)	0.867
REL2	I feel that AI chatbots are tools that support the collection of necessary information	0.865
REL3	AI chatbots are suitable for my habit of online information searching	0.879
REL4	Using AI chatbots satisfies my information needs	0.84
Information credibility (Luo et al., 2013)		
ICR1	I find that information from AI chatbots is as credible as information provided by employees	0.9
ICR2	I find that information from AI chatbots is trustworthy	0.91

Table 2 Measurement model results (continued)

Items	Observation variables	Loadings
ICR3	Information from AI chatbots is as reliable as other sources (e.g., websites, social networks, and m-applications)	0.899
Trust (Awad & Ragowsky, 2008)		
TRT1	I feel safe when using AI chatbots	0.88
TRT2	I do not need to wait for a long time when I make request to AI chatbots	0.91
TRT3	AI chatbots do not disclose and share my personal information with anyone else	0.901
Information usefulness (Sussman & Siegal, 2003), (Park, 2020)		
PUS1	I feel that AI chatbot-based information ~~from~~ is very useful	0.887
PUS2	AI chatbot-based information helps me make purchase decisions quickly	0.87
PUS3	AI chatbot-based information helps me make purchase decisions effectively	0.874
Perceived intelligence (Bartneck et al., 2009), (Le, 2023)		
PIN1	AI chatbots are fully equipped information to respond to my questions	0.878
PIN2	AI chatbots clearly understand and answer exactly my question	0.939
PIN3	AI chatbots are always ready to assist me anytime and anywhere	0.887
Usage intention toward AI chatbots (Davis, 1989), (Le, 2023)		
UIC1	I will use AI chatbots to search for information and solve necessary problems	0.883
UIC2	I plan to use AI chatbots in the future	0.898
UIC3	I will introduce AI chatbots to other users	0.896

Source: Authors' own work

Furthermore, the study measured discriminant validity, as proposed by Fornell and Larcker (1981). A comparison between the calculated square root of AVE and the correlations between constructs was conducted. The results demonstrated that the square root of AVE is larger than the correlations of the constructs (see Table 3).

Consequently, this study ensured the discriminant validity. Additionally, the results from bootstrapping with 5,000 samples showed that none of the confidence intervals of the factors contained the value 1 (significance level α = 5%). Therefore, the study achieved discriminant validity.

Table 3 Discriminant validity, Cronbach's alpha, CR, and AVE

	α	**AVE**	**CR**	**ACC**	**REL**	**ICR**	**TRT**	**PUS**	**PIN**	**UIC**
ACC	0.933	0.78	0.934	0.883						
REL	0.921	0.745	0.921	0.581	0.863					
ICR	0.93	0.815	0.93	0.309	0.407	0.903				
TRT	0.925	0.805	0.925	0.65	0.609	0.532	0.897			
PUS	0.909	0.796	0.909	0.647	0.678	0.442	0.714	0.892		
PIN	0.927	0.813	0.929	0.659	0.651	0.378	0.651	0.748	0.902	
UIC	0.921	0.796	0.921	0.528	0.602	0.391	0.653	0.714	0.757	0.892

Note: ACC= Information accuracy, REL= Information relevance, ICR= Information credibility, TRT= Trust, PUS= Information usefulness, PIN= Perceived intelligence, UIC= Usage intention toward AI chatbots.

Source: Authors' own work

Model Fit

Multiple fit indices were used to assess the model fit, including Chi-square value and its associated degrees of freedom (χ2/df), comparative fit index (CFI), goodness of fit index (GFI), Tucker-Lewis index (TLI), incremental fit index (IFI), relative fit index (RFI), normed fit index (NFI), and root mean square error of approximation (RMSEA). According to Hair et al. (2018), these criteria should satisfy the suggested threshold, including χ2/df ≤ 3; CFI, GFI, TLI, IFI, RFI, and NFI ≥ 0.9; while RMSEA ≤ 0.08 (Table 4). Results showed that all criteria meet the requirements. Therefore, this study ensured the goodness-of-fit.

Table 4 Fitness of research model

Fit Indices	Cut-off standard	Structural model
χ^2/df	≤ 3	1.335
CFI	≥ 0.9	0.989
GFI	≥ 0.9	0.926
TLI	≥ 0.9	0.987
IFI	≥ 0.9	0.989
RFI	≥ 0.9	0.951
NFI	≥ 0.9	0.958
RMSEA	≤ 0.08	0.033

Source: Authors' own work

Structural Model

The coefficient of determination (R^2) assesses the model quality. The research model explained 66.8%, 61.2%, and 63.3% of the variables in information usefulness, trust, and usage intention toward AI chatbots (see Figure 2). Accordingly, the model's explanatory level is relatively good.

Information accuracy positively affects trust (β = 0.329; $p < 0.001$) and information usefulness (β = 0.221; $p < 0.001$); therefore, H1a and H1b are supported. Furthermore, information relevance significantly affects trust (β = 0.161; $p < 0.01$) and information usefulness (β = 0.258; $p < 0.01$); therefore, H2a and H2b are supported. Similarly, the study supports H3a and H3b when information credibility positively affects trust (β = 0.247; $p < 0.001$) and information usefulness (β = 0.115; $p < 0.001$).

Furthermore, trust (β = 0.198; $p < 0.01$) and information usefulness (β = 0.237; $p < 0.01$) have a significantly positive influence on usage intention toward AI chatbots. Thus, H4 and H5 are supported. Additionally, perceived intelligence positively influences information usefulness (β = 0.473; $p < 0.001$), trust (β = 0.263; $p < 0.001$), and AI chatbot usage intention (β = 0.53; $p < 0.001$), thereby supporting H6−H8 (shown in Figure 2 and Table 5).

Table 5 Results of hypothesis testing

Hypothesis	Path Coefficient	*β*	*t*-value	*p*-value	Results
H1a	ACC → TRT	0.329***	5.135	0.000	Supported
H1b	ACC → PUS	0.221***	3.475	0.000	Supported
H2a	REL → TRT	0.161**	2.593	0.010	Supported
H2b	REL → PUS	0.258***	4.087	0.000	Supported
H3a	ICR → TRT	0.247***	5.887	0.000	Supported
H3b	ICR → PUS	0.115**	2.757	0.006	Supported
H4	TRT → UIC	0.198**	3.153	0.002	Supported
H5	PUS → UIC	0.237**	3.251	0.001	Supported
H6	PIN → PUS	0.473***	6.367	0.000	Supported
H7	PIN → TRT	0.263***	3.654	0.000	Supported
H8	PIN → UIC	0.53***	6.075	0.000	Supported

Note: **p-value < 0.01, ***p-value < 0.001, ACC= Information accuracy, REL= Information relevance, ICR= Information credibility, TRT= Trust, PUS= Information usefulness, PIN= Perceived intelligence, UIC= Usage intention toward AI chatbots.

Source: Authors' own work

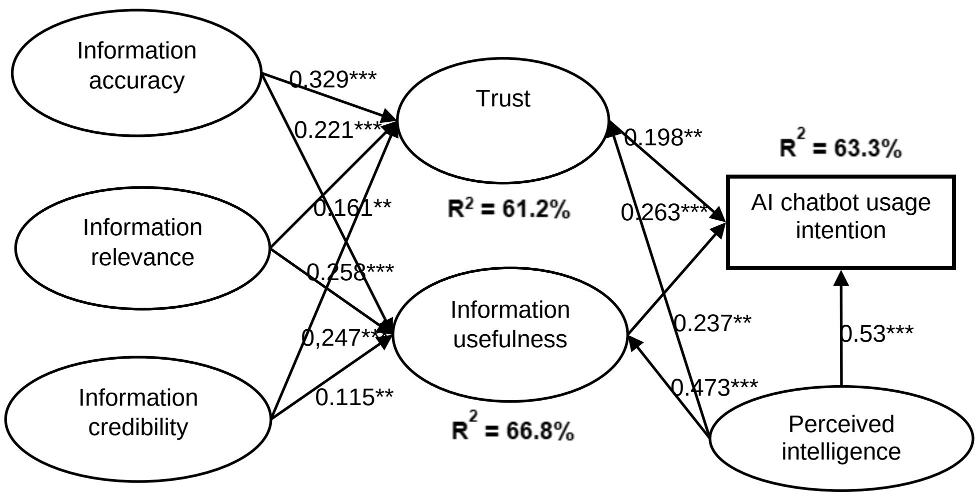

Figure 2 Model testing results.

Source: Authors' own work

Discussion and Implications

Theoretical implications

The study draws several theoretical contributions. This research confirms the applicability of the ELM in the context of digital technologies, particularly in explaining customers' usage intention toward AI chatbots in Vietnam. Additionally, the study suggests that perceived intelligence is a pivotal characteristic of AI chatbots and promotes information usefulness, customer trust, and the intention to embrace AI chatbots for customer−firm communication and online purchase.

First, this study reveals an insightful mechanism for forming customer trust and information usefulness toward AI chatbots. Information accuracy serves as a key motivator of customer trust and information usefulness. These findings are aligned with preliminary studies (Huo et al., 2018; Shang et al., 2021; Xing & Jiang, 2024). This hints that when customers perceive AI chatbot-related information as accurate and precise, they will likely transfer trust and increase their perceptions of information value toward AI chatbots. Chatbots are designed to replace humans in providing immediate and practical assistance to customer inquiries. These chatbots address limitations of human capabilities, such as time constraints, errors, health issues, and complex problem-solving.

Furthermore, the results reveal that information relevance positively affects both trust and perceived usefulness of information in AI chatbots. When customers perceive the information provided by AI chatbots as relevant, they are more likely to express trust and view AI chatbots as genuinely helpful. When customers seek product-related information, AI chatbots respond promptly, have real-time conversations, and provide customized answers. AI chatbots disseminate necessary and timely information, engaging customers with human employees. This perception of usefulness and trust in AI chatbots' ability to provide essential information supports customers' effective shopping decisions. These findings are consistent with previous studies (Park, 2020; Thomas et al., 2019).

Additionally, the results indicate a positive influence of information credibility on customer trust and information usefulness in AI chatbots. This means that if users perceive information from AI chatbots as trustworthy, similar in reliability to information provided by sellers and employees, they will regard information sources as credible and valuable for online purchase. AI chatbots are designed to represent firms and deliver accurate, relevant, and credible information using human-like programming. Consequently, AI chatbots contribute to the credibility of information sources, which is crucial for enhancing customers' trust and perception of information usefulness. These findings reinforce empirical evidence of previous research (Dung et al., 2021; Huo et al., 2018; Park, 2020; Zhu et al., 2016).

Second, this study explains usage intention toward AI chatbots through the positive influence of trust, information usefulness, and perceived intelligence. Among these factors, perceived intelligence ($\beta = 0.53$; $p < 0.001$) is of paramount importance in triggering intention to use AI chatbots, followed by information usefulness ($\beta = 0.237$; $p < 0.01$) and trust ($\beta = 0.198$; $p < 0.01$). Intelligence is a vital feature of AI chatbots, enabling them to handle requests, understand customer needs, respond promptly, and address complicated issues that might be challenging for humans. Thus, perceived intelligence strongly promotes customers' engagement in AI chatbots. This finding agrees with the arguments of earlier studies (e.g., Pillai and Sivathanu (2020)).

Furthermore, information usefulness significantly affects customers' intention to use AI chatbots. According to previous research (Cu, 2021; Park, 2020), information usefulness is key in fostering customers' willingness to adopt AI chatbots. Customers who recognize the benefits of AI chatbots such as timely responses, information quality, and 24/7 availability – would be more likely to accept and utilize them. Additionally, trust is an essential predictor of intention to use AI chatbots. Extant studies empirically substantiated the positive relationship (Chen et al., 2021; Mostafa & Kasamani, 2022; Nyagadza et al., 2022; Silva et al., 2023). It can be confidently argued that the adoption of AI chatbots and purchase decisions depend on customer trust in the information provided. Customers who perceive AI chatbot information as comparable to information from employees and other sources (e.g., websites, mobile applications, and relatives) are more likely to trust AI chatbots. Customers who find AI chatbot-based information different from other sources will pay less attention and lessen their willingness to utilize AI chatbots.

Practical Implications

Based on the above findings, the study offers several practical suggestions to trigger customer acceptance of AI chatbots. First, the positive impact of information accuracy on trust and information usefulness underscores the need for chatbot developers to focus on improving the functionality related to providing confidential, objective, and accurate product-related information because customers' perceptions of information value are crucial in fostering their readiness to utilize these chatbots in online purchase (Cheng & Jiang, 2022; Thomas et al., 2019). Additionally, information relevance, which was shown to facilitate trust and information usefulness, requires AI chatbot developers to anticipate and understand customers' personalized needs, preferences, and concerns. Firms must provide customers with relevant, up-to-date, timely, and customized information via AI chatbots. For instance, available information such as product prices, payment methods, promotions, and customer support services should be regularly updated. Firms should avoid dispersing a large amount of information to customers via AI chatbots because the excessive content would diminish information credibility, customers' trust, and willingness to utilize AI chatbots and purchase products (Le, 2023). Furthermore, firms should ensure consistent information displayed across various communication channels, including social networks, websites, mobile applications, and AI chatbots. In the present early stages of AI chatbot use in Vietnam, customers may not fully trust information through AI chatbots, leading them to seek out and compare information from different sources. If customers assess the consistency and reliability of information across various channels, they are more likely to express their trust and positive perception of the information value of AI chatbots. Moreover, practitioners strive to promote AI chatbots' advantages to target customers (e.g., young consumers and users with immature online purchase experiences) by creating opportunities that help them follow their services on a daily basis.

Additionally, technology developers attempt to diversify the communication modes of text- and voice-based AI chatbots that offer customers customized services. With AI chatbots being in the embryonic stage, the assistance should be helpful for customers via FAQs, websites, social media, and even humans. Accordingly, this supporting integration would enhance customer trust and address technical issues of AI chatbots in Vietnam. Moreover, developers should focus on advancing features such as human-like understanding and problem-solving capabilities.

Limitations and Future Research

In addition to the above-outlined contributions, the study acknowledges some limitations and suggests several avenues for future research. First, while AI chatbots are still in the infant stage in Vietnam, customer coverage will remain low. Consequently, population representativeness is limited and does not generate the generalization of the findings. To acquire the more comprehensive understanding of AI chatbot usage behavior, future research should increase the sample size with diverse participants. Second, the current research primarily focused on students (with 49.51% of the respondents) who have gained familiarity with using the Internet and advanced technologies in the digital transformation context. Future studies should broaden the survey subjects to include a more diverse range of AI chatbot users, as the demand for information searching and online purchases via AI chatbots is rising. Third, while this study employed the ELM to explicate AI chatbot use intention through integrating both the central and peripheral routes and AI chatbots' intelligence, there is room for further exploration in the domain of AI chatbot usage behavior. Hence, the incorporation of complementary dimensions from these routes into other AI chatbot characteristics, such as interactivity, automation, customization, and perceived anthropomorphism, to offer holistic insights into customers' behavioral responses toward AI chatbots (Chen et al., 2021; Cheng et al., 2024; Nyagadza et al., 2022; Yang & Lee, 2019). Lastly, future research could elucidate the indispensability of AI chatbots by empirically examining the correlation between usage intention and purchase intention in AI chatbots.

Acknowledgements

This study is supported by a grant from the Ministry of Education and Training, Vietnam, and Thuongmai University [No.B2025-TMA-03].

References

Ajzen, I., & Driver, B. L. (1991). Prediction of leisure participation from behavioral, normative, and control beliefs: an application of the theory of planned behavior. *Leisure Sciences, 13*(3), 185-204. https://doi.org/10.1080/01490409109513137

Al-Omairi, L., Al-Samarraie, H., Alzahrani, A. I., & Alalwan, N. (2021). Students' intention to adopt e-government learning services: a developing country perspective. *Library Hi Tech, 39*(1), 308-334. https://doi.org/10.1108/LHT-02-2020-0034

Anderson, J. C., & Gerbing, D. (1988). Structural equation modeling in practice: a review of recommended two-step approach. *Psychological Bulletin, 103*(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411

Awad, N. F., & Ragowsky, A. (2008). Establishing trust in electronic commerce through online word of mouth: an examination across genders. *Journal of Management Information Systems, 24*(4), 101-121. https://doi.org/10.2753/MIS0742-1222 240404

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics, 1*(1), 71-81. https://doi.org/10.1007/s12369-008-0001-3

Chatterjee, S., & Sreenivasulu, N. S. (2023). Impact of AI regulation and governance on online personal data sharing: from sociolegal, technology and policy perspective. *Journal of Science and Technology Policy Management, 14*(1), 157-180. https://doi.org/10.1108/JSTPM-07-2020-0103

Chen, J.-S., Le, T.-T.-Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management, 49*(11), 1512-1531. https://doi.org/10.1108/IJRDM-08-2020-0312

Chen, Q., Yin, C., & Gong, Y. (2023). Would an AI chatbot persuade you? An empirical answer from the elaboration likelihood model. *Information Technology & People, ahead-of-print*(ahead-of-print). doi:https://doi.org/10.1108/ITP-10-2021-0764

Cheng, X., Qiao, L., Yang, B., & Li, Z. (2024). An investigation on the influencing factors of elderly people's intention to use financial AI customer service. *Internet Research, 34*(3), 690-717. https://doi.org/10.1108/INTR-06-2022-0402

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management, 31*(2), 252-264. https://doi.org/10.1108/JPBM-05-2020-2907

Chin, W. W., Gopal, A., & Salisbury, W. D. (1997). Advancing the theory of adaptive structuration: the development of a scale to measure faithfulness of appropriation. *Information Systems Research, 8*(4), 342-367. https://doi.org/10.1287/isre.8.4.342

Cu, L. X. (2021). Information value in social media: an integrated approach to preventive behaviors under COVID-19. *VNU Journal of Science: Economics and Business, 1*(3), 1-9. https://doi.org/10.25073/2588-1108/vnueab.4636

Cu, L. X., & Wang, H. (2020). Integrative perceived values influencing consumers' attitude and behavioral responses toward mobile location-based advertising: an empirical study in Vietnam. *Asia Pacific Journal of Marketing and Logistics, 33*(1), 275-295. https://doi.org/10.1108/APJML-08-2019-0475

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Dung, M. N., Chiu, Y.-T. H., & Le, H. D. (2021). Determinants of continuance intention towards banks' chatbot services in Vietnam: a necessity for sustainable development. *Sustainability, 13*(14), 7625. https://doi.org/10.3390/su13147625

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey. *International Journal of Bank Marketing, 39*(2), 294-311. https://doi.org/10.1108/IJBM-02-2020-0056

Filieri, R., Chen, W., & Lal Dey, B. (2017). The importance of enhancing, maintaining and saving face in smartphone repurchase intentions of Chinese early adopters: an exploratory study. *Information Technology & People, 30*(3), 629-652. https://doi.org/10.1108/ITP-09-2015-0230

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.2307/3151312

Hair, F., Babin, B., Black, W. J., & Anderson, R. E. (2018). *Multivariate data analysis*. Australia: Cengage.

Huo, C., Zhang, M., & Ma, F. (2018). Factors influencing people's health knowledge adoption in social media. *Library Hi Tech, 36*(1), 129-151. https://doi.org/10.1108/LHT-04-2017-0074

Jain, S., & Gandhi, A. V. (2021). Impact of artificial intelligence on impulse buying behaviour of Indian shoppers in fashion retail outlets. *International Journal of Innovation Science, 13*(2), 193-204. https://doi.org/10.1108/IJIS-10-2020-0181

Le, X. C. (2023). Inducing AI-powered chatbot use for customer purchase: the role of information value and innovative technology. *Journal of Systems and Information Technology, 25*(2), 219-241. https://doi.org/10.1108/JSIT-09-2021-0206

Le, X. C. (2025a). What determines learners' active participation in Metaverse-based learning in an emerging market. *Library Hi Tech, ahead-of-print*(ahead-of-print). https://doi.org/10.1108/LHT-06-2024-0300

Le, X. C. (2025b). Older consumers' positive word-of-mouth toward m-banking: evidence from an emerging market. *Journal of Science and Technology Policy Management, ahead-of-print*(ahead-of-print). https://doi.org/10.1108/JSTPM-06-2023-0103

Luo, C., Luo, X., Schatzberg, L., & Sia, C. L. (2013). Impact of informational factors on online recommendation credibility: the moderating role of source credibility. *Decision Support Systems, 56*, 92-102. https://doi.org/10.1016/j.dss.2013.05.005

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing, 56*(6), 1748-1771. https://doi.org/10.1108/EJM-02-2020-0084

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2021). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electronic Markets, 31*(2), 343-364. https://doi.org/10.1007/s12525-020-00411-w

Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of Management Information Systems, 21*(4), 199-235. https://doi.org/10.1080/07421222.2005.11045823

Nguyen, T. H., & Le, X. C. (2025). Artificial intelligence-based chatbots – a motivation underlying sustainable development in banking: standpoint of customer experience and behavioral outcomes. *Cogent Business & Management, 12*(1), 2443570. https://doi.org/10.1080/23311975.2024.2443570

Nguyen, T. H., & Le, X. C. (2021). How social media fosters the elders' COVID-19 preventive behaviors: perspectives of information value and perceived threat. *Library Hi Tech, 39*(3), 776-795. https://doi.org/10.1108/LHT-09-2020-0241

Nguyen, T. T., Le, A. D., Hoang, H. T., & Nguyen, T. (2021). NEU-chatbot: chatbot for admission of National Economics University. *Computers and Education: Artificial Intelligence, 2*, 100036. https://doi.org/10.1016/j.caeai.2021.100036

Nguyen, V. T., Phong, L. T., & Chi, N. T. K. (2023). The impact of AI chatbots on customer trust: an empirical investigation in the hotel industry. *Consumer Behavior in Tourism and Hospitality, 18*(3), 293-305. https://doi.org/10.1108/CBTH-06-2022-0131

Nyagadza, B., Muposhi, A., Mazuruse, G., Makoni, T., Chuchu, T., Maziriri, E. T., & Chare, A. (2022). Prognosticating anthropomorphic chatbots' usage intention as an e-banking customer service gateway: cogitations from Zimbabwe. *PSU Research Review, 8*(2), 356-372. https://doi.org/10.1108/PRR-10-2021-0057

Park, E. (2020). User acceptance of smart wearable devices: an expectation-confirmation model approach. *Telematics and Informatics, 47*, 101318. https://doi.org/10.1016/j.tele.2019.101318

Park, Y., Kim, J., Jiang, Q., & Kim, K. H. (2024). Impact of artificial intelligence (AI) chatbot characteristics on customer experience and customer satisfaction. *Journal of Global Scholars of Marketing Science, 34*(3), 439-457. https://doi.org/10.1080/21639159.2024.2362654

Petty, R. E., Cacioppo, J. T., & Goldman, R. (1981). Personal involvement as a determinant of argument-based persuasion. *Journal of Personality and Social Psychology, 41*(5), 847-855. https://doi.org/10.1037/0022-3514.41.5.847

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management, 32*(10), 3199-3226. https://doi.org/10.1108/IJCHM-04-2020-0259

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Rotchanakitumnuai, S., & Speece, M. (2023). Conceptualizing a framework for social media data sharing. *Thammasat Review, 26*(1), 244-266. https://doi.org/10.14456/tureview.2023.10

Roy, K., Paul, U. K., Tiwari, S., & Mookherjee, A. (2024). Impact of electronic word of mouth (e-WOM) on purchasing decisions: an empirical study. *Benchmarking: An International Journal, ahead-of-print*(ahead-of-print). https://doi.org/10.1108/BIJ-08-2024-0642

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services, 68*, 103059. https://doi.org/10.1016/j.jretconser.2022.103059

Sarkar, J. G., & Sarkar, A. (2019). Young adult consumers' involvement in branded smartphone based service apps: investigating the roles of relevant moderators. *Information Technology & People, 32*(6), 1608-1632. https://doi.org/10.1108/ITP-04-2017-0128

Shang, L., Zhou, J., & Zuo, M. (2021). Understanding older adults' intention to share health information on social media: the role of health belief and information processing. *Internet Research, 31*(1), 100-122. https://doi.org/10.1108/INTR-12-2019-0512

Silva, S. C., De Cicco, R., Vlačić, B., & Elmashhara, M. G. (2023). Using chatbots in e-retailing – How to mitigate perceived risk and enhance the flow experience. *International Journal of Retail & Distribution Management, 51*(3), 285-305. https://doi.org/10.1108/IJRDM-05-2022-0163

Statista. (2022). Chatbot market size worldwide 2018-2027. Retrieved from https://www.statista.com/statistics/1007392/worldwide-chatbot-market-size/

Steenkamp, J.-B. E. M., & Baumgartner, H. (2000). On the use of structural equation models for marketing modeling. *International Journal of Research in Marketing, 17*(2), 195-202. https://doi.org/10.1016/S0167-8116(00)00016-1

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: an integrated approach to knowledge adoption. *Information Systems Research, 14*(1), 47-65. https://doi.org/10.1287/isre.14.1.47.14767

Thomas, M.-J., Wirtz, B., & Weyerer, J. (2019). Determinants of online review credibility and its impact on consumers' purchase intention. *Journal of Electronic Commerce Research, 20*, 1-21. doi:http://www.jecr.org/sites/default/files/2019 vol20no1_Paper1.pdf

VietnamPlus. (2025, February 20). *Vietnamese retailers accelerate digital transformation*. Vietnamplus. https://en.vietnamplus.vn/vietnamese-retailers-accelerate-digital-transformation-post310243.vnp

Xing, J., & Jiang, Q. (2024). Factors influencing user experience in AI chat systems – a satisfaction study based on factor analysis and linear regression. *Kybernetes, ahead-of-print*(ahead-of-print). https://doi.org/10.1108/K-10-2023-2237

Yang, H., & Lee, H. (2019). Understanding user behavior of virtual personal assistant devices. *Information Systems and e-Business Management, 17*(1), 65-87. https://doi.org/10.1007/s10257-018-0375-1

Yen, C.-S., Chen, G.-L., Kang, C.-C., Wang, Y.-H., & Yang, S.-C. (2024). Investigating factors that influence purchase intentions in live-streaming contexts through the elaboration likelihood model: the perspectives of para-social interaction and information quality. *The Review of Socionetwork Strategies*. https://doi.org/10.1007/s12626-024-00166-2

Zhou, T. (2016). Understanding location-based services continuance: an IS success model perspective. *International Journal of Mobile Communications, 14*(6), 553-567. https://doi.org/10.1504/IJMC.2016.079300

Zhu, D. H., Chang, Y. P., & Luo, J. J. (2016). Understanding the influence of C2C communication on purchase decision in online communities from a perspective of information adoption model. *Telematics and Informatics, 33*(1), 8-16. https://doi.org/10.1016/j.tele.2015.06.001