“Explaining purchase intention in AI-powered e-commerce chatbots: An integrative model of functional, experiential, and credibility drivers”

AUTHORS	Muinah Fadhilah Ratih Kusumawardhani Ambar Lukitaningsih
ARTICLE INFO	Muinah Fadhilah, Ratih Kusumawardhani and Ambar Lukitaningsih (2026). Explaining purchase intention in AI-powered e-commerce chatbots: An integrative model of functional, experiential, and credibility drivers. *Innovative Marketing* , *22*(3), 1–20. doi:10.21511/im.22(3).2026.01
DOI	http://dx.doi.org/10.21511/im.22(3).2026.01
RELEASED ON	Friday, 03 July 2026
RECEIVED ON	Tuesday, 30 September 2025
ACCEPTED ON	Tuesday, 07 April 2026
LICENSE	
JOURNAL	"Innovative Marketing "
ISSN PRINT	1814-2427
ISSN ONLINE	1816-6326
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
61	**1**	**8**

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Muinah Fadhilah (Indonesia), **Ratih Kusumawardhani** (Indonesia),
Ambar Lukitaningsih (Indonesia)

EXPLAINING PURCHASE INTENTION IN AI-POWERED E-COMMERCE CHATBOTS: AN INTEGRATIVE MODEL OF FUNCTIONAL, EXPERIENTIAL, AND CREDIBILITY DRIVERS

Abstract

Artificial intelligence-based chatbots are increasingly used on e-commerce platforms to improve customer interactions and service efficiency, yet their effectiveness in influencing consumer purchase intentions in emerging markets remains insufficiently understood. This study aims to examine how interaction, entertainment, perceived enjoyment, service quality, perceived ease of use, trendiness, communication competence, and credibility influence purchase intention, mediated by customer satisfaction, in the context of Tokopedia's AI chatbot in Indonesia. The study employed a quantitative approach using a structured online survey of 240 Tokopedia users in Yogyakarta and Central Java conducted between March and July 2024, and the collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that communication competence ($\beta = 0.287$, $p < 0.001$), credibility ($\beta = 0.254$, $p < 0.001$), and trendiness ($\beta = 0.231$, $p < 0.01$) are the strongest predictors of customer satisfaction and indirectly influence purchase intention. Service quality ($\beta = 0.214$, $p < 0.001$) and perceived ease of use ($\beta = 0.198$, $p < 0.01$) also significantly contribute to satisfaction, while entertainment ($\beta = 0.176$, $p < 0.05$) and perceived enjoyment ($\beta = 0.169$, $p < 0.05$) enhance the experiential aspect of chatbot interaction. Satisfaction demonstrates a strong positive effect on purchase intention ($\beta = 0.412$, $p < 0.001$), confirming its mediating role in translating chatbot service attributes into behavioral outcomes. These findings suggest that effective AI chatbot design should integrate functional service quality with relational and experiential communication capabilities to strengthen consumer engagement and purchasing behavior on e-commerce platforms.

Keywords AI chatbots, satisfaction, purchase intention, customer satisfaction, e-commerce, PLS-SEM, Indonesia

JEL Classification M31, L81, L86, O33

Type of the article: Research Article

Received on: 30th of September, 2025
Accepted on: 7th of April, 2026
Published on: 3rd of July, 2026

Muinah Fadhilah, Lecturer, Faculty of Economy, Magister Management, Universitas Sarjanawiyata Tamansiswa [Sarjanawiyata Tamansiswa University], Indonesia. (Corresponding author)

Ratih Kusumawardhani, Lecturer, Faculty of Economy, Department of Management, Universitas Sarjanawiyata Tamansiswa [Sarjanawiyata Tamansiswa University], Indonesia.

Ambar Lukitaningsih, Lecturer, Assoc. Proffesor, Faculty of Economy, Department of Management, Universitas Sarjanawiyata Tamansiswa [Sarjanawiyata Tamansiswa University], Indonesia.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

The advancement of artificial intelligence (AI) has revolutionized digital customer service, particularly through the deployment of chatbots in e-commerce platforms. These AI-powered systems are designed to facilitate real-time interaction, address consumer inquiries, resolve transactional problems, and provide detailed product information with efficiency and speed (Grewal et al., 2021; Na et al., 2021). However, despite these technological benefits, AI chatbots still face significant barriers in fostering emotional connection, user satisfaction, and ultimately, purchase intention.

A prominent example of this innovation in Indonesia is Tokopedia's chatbot (TANYA), which has been integrated into its mobile and web platforms to automate customer support services. As one of the leading e-commerce platforms in Indonesia, Tokopedia serves millions of users monthly, and the effectiveness of TANYA plays a critical role in shaping user experience and behavioral outcomes. However, local user behaviors, language nuances, and trust issues with AI-based systems highlight a gap between technology deployment and user receptivity in Indonesian contexts.

Previous studies have extensively examined technical dimensions such as perceived ease of use, responsiveness, and communication credibility. Nevertheless, few have holistically addressed the combined influence of technical (e.g., ease of use, quality of service), hedonic (e.g., entertainment, perceived enjoyment), and affective (e.g., emotional engagement, satisfaction) dimensions on purchase intention, particularly using satisfaction as a central mediating variable. Furthermore, the majority of existing research has been conducted in international or tourism-related (Akter et al., 2022; Belanche et al., 2019; Beyari & Garamoun, 2022; Chowdhury et al., 2025; Chung et al., 2020), lacking contextual relevance to Indonesian e-commerce ecosystems.

Thus, the central scientific problem emerges: AI chatbots are increasingly embedded in digital commerce, yet the theoretical and empirical foundations explaining how users in emerging markets interpret, evaluate, and emotionally respond to these interactions remain incomplete. This gap highlights the need to conceptualize AI-driven service encounters not only as technical systems but also as socio-psychological phenomena shaped by cultural, communicative, and experiential factors. Building on these gaps, the present study proposes an integrated framework explaining how users evaluate AI-powered chatbot services in e-commerce. Specifically, the study examines the combined effects of functional attributes (service and information quality, perceived usefulness, and ease of use), experiential attributes (interaction, entertainment, and trendiness), and credibility-related attributes (communication competence and credibility) on customer satisfaction and purchase intention. Using Tokopedia's chatbot as the empirical context, this research aims to clarify how these multidimensional factors jointly share consumer decision-making in AI-mediated commerce within an emerging digital market.

1. LITERATURE REVIEW AND HYPOTHESES

Understanding how users evaluate AI-driven chatbot interactions is central to explaining behavioral outcomes in conversational commerce. In digital environments where human agents are replaced by algorithmic systems, interaction quality becomes the primary interface through which users form cognitive and emotional judgments. Therefore, examining interaction as a multidimensional construct is essential to achieving the study's objective of explaining satisfaction and purchase intention in AI-mediated e-commerce.

Interaction in AI-driven platforms refers to the perceived quality of communication and responsiveness between users and chatbots, including human likeness, empathy, and contextual relevance (Adam et al., 2021; Ghazali et al., 2020). Within the SOR framework, interaction serves as a stimulus that shapes users' internal states, such as trust, confidence, and comfort, which then influence behavioral responses like purchase intention (Mehrabian & Russell, 1974). High-quality interactions, characterized by responsiveness and personalization, reduce uncertainty, strengthen engagement, and increase users' willingness to transact (Prentice et al., 2020). Prior studies show that personalized chatbot communication improves attitudes and purchase intention (Brandtzaeg & Folstad, 2018; Chung et al., 2020), while seamless interaction reduces cognitive load and encourages transactional behavior (Chen et al., 2023).

On Tokopedia, TANYA's ability to mimic human conversation and provide timely assistance helps reduce confusion and supports users' confidence in completing purchases. Interaction quality also plays a central role in shaping satisfaction. It reflects users' perceptions of how naturally, accurately, and meaningfully the chatbot communicates (Chen et al., 2023). Studies show that empathetic, prompt, and informative responses enhance users' evaluations of digital service encounters and increase satisfaction (Adam et al., 2021; Prentice

http://dx.doi.org/10.21511/im.22(3).2026.01

et al., 2020). In e-commerce, human-like conversational flow and coherent dialogue improve perceived service quality, reduce frustration, and promote loyalty (Luo et al., 2019; Mariani et al., 2023). For Tokopedia users, real-time and contextually relevant responses from TANYA create a relational experience in which users feel heard and supported, leading to higher satisfaction.

In emerging e-commerce markets, interaction quality may carry even greater weight as trust in AI technologies develops. When chatbot responses are timely, contextually relevant, and conversationally smooth, users experience reduced ambiguity and greater confidence in decision-making. Such interaction characteristics transform chatbot engagement from a mechanical exchange into a relational experience, thereby strengthening satisfaction and increasing purchase intention. These insights suggest that interaction quality functions not only as a technical attribute but also as a psychological catalyst in AI-enabled commerce.

As conversational commerce evolves, user engagement is no longer driven solely by efficiency and task completion. Digital platforms increasingly integrate entertainment elements into service encounters, transforming transactional exchanges into immersive experiences. Within this context, entertainment reflects the extent to which chatbot interactions are perceived as enjoyable, playful, and emotionally stimulating, extending beyond utilitarian functionality.

Entertainment refers to the extent to which interactions with AI systems such as chatbots are perceived as enjoyable, fun, and emotionally engaging. As digital commerce increasingly merges with entertainment, hedonic experience becomes a key driver of consumer decision-making (Huang & Benyoucef, 2013). Grounded in the Uses and Gratification (U&G) Theory, users actively seek digital interactions that fulfil emotional and hedonic needs (Ruggiero, 2000). Chatbots enriched with humor, gamified responses, emojis, and human-like personality traits stimulate enjoyment, reduce stress, and create positive affective states that elevate purchase intention (Ashfaq et al., 2020; Chung et al., 2020).

Empirical evidence consistently shows that entertaining chatbot interactions enhance user engagement and willingness to purchase (Moriuchi, 2019; Tsai et al., 2021). Hedonic cues reduce uncertainty and foster emotional connection, making entertainment a persuasive stimulus that supports consumer decisions. Entertainment is also an important determinant of satisfaction in AI-driven services. Beyond functional performance, users value enjoyable and lively interactions that provide psychological stimulation and human-like engagement (Thong et al., 2006). Studies show that entertaining elements such as humor, emojis, and gamified dialogue improve emotional responses and satisfaction (Grewal et al., 2021; Moriuchi, 2019). In platforms like Tokopedia, such features elevate interactions from transactional to effectively rewarding experiences.

Perceived enjoyment refers to the pleasure and intrinsic satisfaction users feel when interacting with a system, regardless of performance outcomes (Davis et al., 1992). In AI-based e-commerce, enjoyment emerges as a key experiential factor shaping user satisfaction. Chatbot interactions become enjoyable when they are smooth, responsive, and enriched with features such as humor, personalized messages, and an empathetic tone, providing emotional gratification beyond task completion. Aligned with the Technology Acceptance Model (TAM), enjoyment functions as an intrinsic motivator that drives continued technology use (van der Heijden, 2004; Venkatesh, 2000).

Empirical evidence shows that higher perceived enjoyment increases satisfaction and sustained usage (Chung et al., 2020; Moriuchi, 2019; Tsai et al., 2021). In Indonesia's e-commerce setting, enjoyable interactions – such as those offered by Tokopedia's TANYA chatbot through friendly language and real-time responses – enhance emotional engagement and elevate user evaluations of the service. Thus, enjoyment acts as an emotional amplifier, transforming user experience from simple acceptance to genuine delight.

In the Indonesian e-commerce context, where users often seek efficiency coupled with emotional engagement, perceived enjoyment plays a decisive role in evaluating chatbot services. Tokopedia's TANYA chatbot, for example, may incorporate user-friendly dialogues, relatable language, and real-time responses that foster enjoyable interactions.

When such experiences align with users' expectations for convenience and entertainment, the result is greater satisfaction with the overall service. In this sense, enjoyment serves as an emotional amplifier, elevating user perception from mere acceptance to delight.

Service quality remains a foundational determinant of customer evaluation across service settings, including digital and AI-mediated environments. In conversational commerce, where human agents are replaced by algorithmic systems, perceived service quality becomes the primary benchmark through which users assess platform reliability. While traditional service quality models emphasize reliability, responsiveness, assurance, and empathy, digital contexts require an expanded interpretation that incorporates response speed, informational accuracy, contextual adaptability, and consistency in automated communication (Grewal et al., 2021; Parasuraman et al., 1988).

Quality of service (QoS) is a key determinant of user experience and satisfaction in digital environments, including AI-based chatbots. In this context, QoS reflects the chatbot's ability to deliver fast, accurate, and contextually appropriate responses (Grewal et al., 2021; Parasuraman et al., 1988). High-quality chatbot service – marked by clarity, relevance, and responsiveness – reduces user uncertainty, builds trust, and enhances satisfaction (Chatterjee et al., 2020; Chung et al., 2020).

Empirical studies show that prompt, consistent, and personalized chatbot responses significantly improve satisfaction (Melián-González et al., 2021; Pillai & Sivathanu, 2020). When AI systems perform at a level comparable to human agents, users often report even higher satisfaction due to reduced friction and quicker issue resolution. In emerging digital markets like Indonesia, where trust in AI is still developing, consistent service quality plays an even more critical role. Effective chatbot performance – through clear communication and strong problem-solving ability – strengthens user confidence and directly enhances satisfaction (Yun & Park, 2022).

Taken together, these insights position service quality as both a functional and relational determinant within AI-driven commerce. It not only directly shapes satisfaction but also indirectly supports behavioral intention by stabilizing users' perceptions of reliability and competence. In chatbot-based environments, maintaining high service quality is therefore not merely an operational requirement but a strategic condition for sustaining customer engagement.

Beyond interaction and service performance, the informational value delivered by AI chatbots plays a decisive role in shaping user evaluations. In digital commerce, where purchase decisions often rely heavily on mediated communication, the accuracy and clarity of information become critical determinants of satisfaction. Information quality refers to the degree to which chatbot responses are precise, relevant, timely, complete, and contextually appropriate. When users perceive information as reliable and meaningful, they are more likely to feel confident in their decision-making.

The quality of information (QoI) is essential to shaping user satisfaction in AI-based e-commerce services. QoI reflects the accuracy, relevance, timeliness, and completeness of information provided by chatbots (Prentice et al., 2020; Yun & Park, 2022). According to the Information Systems Success Model (Delone & McLean, 2003), high-quality information increases user trust, reduces ambiguity, and enhances satisfaction – especially when responses are clear, context-appropriate, and helpful (Alalwan et al., 2020).

Empirical research in chatbot and digital service contexts confirms that structured, personalized, and context-sensitive information significantly enhances user trust and overall experience (Alzahrani & Seth, 2021; Chatterjee et al., 2020). Conversely, vague or inconsistent information leads to frustration and lowers platform credibility. In platforms like Tokopedia, accurate product details, transaction updates, and personalized FAQs enhance user evaluation of the service (Pillai & Sivathanu, 2020). This dynamic aligns with Expectation-Confirmation Theory, which posits that satisfaction increases when perceived performance meets or exceeds prior expectations (Bhattacherjee, 2001). In conversational commerce, confirmation occurs not only through task completion but also through the informational adequacy of chatbot responses.

http://dx.doi.org/10.21511/im.22(3).2026.01

Taken together, information quality operates as both a cognitive stabilizer and a trust-building mechanism in AI-driven e-commerce. By reducing uncertainty and enhancing decision clarity, high-quality information increases satisfaction and users' willingness to proceed with transactions. Therefore, in chatbot-mediated environments, informational precision is not merely supportive but foundational to positive behavioral outcomes.

While interaction quality and informational accuracy shape users' experiential evaluations, perceived usefulness captures the instrumental value of AI chatbot systems. In digital commerce, usefulness reflects the extent to which users believe that chatbot interactions improve efficiency, simplify tasks, and facilitate decision-making. Within the Technology Acceptance Model (TAM), perceived usefulness represents a central determinant of user evaluation, linking functional performance to behavioral outcomes.

Perceived usefulness (PU), a core construct of the Technology Acceptance Model (1989), refers to the extent to which users believe a system enhances their task performance. In AI-powered e-commerce chatbots, PU reflects users' perceptions of how helpful, efficient, and valuable the chatbot is in supporting activities such as product search, inquiry handling, and customer assistance (Alalwan et al., 2020). Prior studies consistently show that when users perceive AI systems as improving efficiency, saving time, and providing relevant information, their satisfaction increases (Alzahrani & Seth, 2021; Chatterjee et al., 2020).

On platforms like Tokopedia, chatbots such as TANYA enhance satisfaction by reducing friction and offering meaningful assistance, thereby reinforcing the emotional value of the service (Xie et al., 2024). Based on Expectation-Confirmation Theory (Bhattacherjee, 2001), satisfaction arises when users' expectations of usefulness are met or exceeded; failure to meet these expectations leads to dissatisfaction. Recent evidence further confirms PU as a strong predictor of satisfaction with AI interactions, particularly among users seeking fast, contextually relevant support (Alshammari & Babu, 2025; Yun & Park, 2022). Thus, optimizing perceived usefulness is essential to enhancing overall user experience in AI-driven customer service.

However, in contemporary conversational commerce, usefulness alone may not be sufficient to explain behavioral intention. Compared to earlier technology adoption settings where utilitarian value dominated, AI chatbot environments blend functional utility with experiential and symbolic dimensions. Thus, perceived usefulness remains a necessary foundation for satisfaction, but it interacts with entertainment, credibility, and interaction quality to shape purchase intention. In this sense, usefulness functions as a cognitive anchor within a broader multidimensional evaluation process.

Taken together, these arguments suggest that optimizing perceived usefulness is essential for sustaining satisfaction in AI-driven e-commerce. Yet its influence must be understood as part of an integrated framework in which efficiency, emotional engagement, and trust collectively determine behavioral outcomes.

In addition to usefulness, the perceived simplicity of interacting with AI systems plays a crucial role in shaping user evaluation. In conversational commerce environments, ease of use reflects how intuitive, clear, and effortless chatbot interactions feel. When users can navigate conversations smoothly, receive understandable responses, and complete tasks without confusion, they are more likely to evaluate the system positively.

Within the Technology Acceptance Model, perceived ease of use functions as a cognitive precursor that lowers effort expectancy and enhances system acceptance. Perceived ease of use (PEOU) refers to the extent to which users believe a technology is effortless to operate (Davis, 1989). In AI-powered chatbot contexts, ease of use is evident in streamlined dialogue structures, rapid response times, and minimal need for repeated clarification. When interactions require little cognitive effort, users experience reduced frustration and greater confidence in system performance. Empirical research in digital services consistently shows that intuitive interfaces and frictionless processes contribute to higher satisfaction and more favorable behavioral intentions (Lynn et al., 2020; Yun & Park, 2022).

Beyond functional efficiency, ease of use also carries psychological implications. Effortless interaction enhances perceived control and lowers technology-related anxiety, especially in AI-mediated environments where users may initially feel uncertainty. Studies in e-commerce and e-banking settings indicate that user-friendly systems foster trust and positive affective responses, reinforcing satisfaction (Almansour & Elkrghli, 2023; Alshammari & Babu, 2025; Yun & Park, 2022). This suggests that ease of use not only reduces operational complexity but also enhances emotional comfort during digital interactions.

However, in contemporary AI chatbot services, ease of use operates alongside other experiential and credibility-based drivers. While earlier technology adoption research often positioned ease of use as a dominant predictor of behavioral intention, its role in conversational commerce appears more complementary. It stabilizes the user experience by minimizing friction, thereby enabling other factors – such as entertainment, interaction quality, and perceived usefulness – to exert stronger influence on satisfaction and purchase intention.

Taken together, perceived ease of use contributes to satisfaction by aligning both functional convenience and psychological comfort. In chatbot-based e-commerce settings, intuitive and seamless interaction is therefore a necessary condition for sustaining positive evaluations and encouraging continued engagement.

As digital commerce evolves within fast-changing technological and cultural landscapes, users increasingly evaluate platforms not only on performance but also on perceived modernity. Trendiness reflects the extent to which a digital service appears current, innovative, and aligned with prevailing social and technological norms. In AI-mediated environments, this perception can shape user attitudes by signaling advancement, relevance, and forward-thinking capability. Trendiness refers to the extent to which users perceive a digital service or AI-based technology as modern, fashionable, and aligned with current technological and social trends (Vahdat et al., 2021).

Perceptions of modernity are particularly salient among digitally native consumers, who often associate contemporary interface design with technological sophistication and social status. When chatbot systems incorporate adaptive responses, informal conversational styles, personalized avatars, or culturally resonant expressions, they may be perceived as more aligned with ongoing digital trends. Such perceptions generate positive affect and reinforce users' sense of belonging to technologically progressive communities (Chung et al., 2020; Foroudi et al., 2018). In this sense, trendiness operates as a symbolic cue that extends beyond functionality (Chung et al., 2020; Foroudi et al., 2018).

In e-commerce settings, chatbots perceived as trendy – through features such as personalized avatars, informal conversation styles, emojis, or AI-driven adaptive responses – enhance both functional and hedonic value, increasing emotional engagement and satisfaction (Haugeland et al., 2022; Jiang et al., 2022). Trendiness also strengthens consumer identity signaling and symbolic consumption, which can increase purchase intention, particularly among digital-native (Islam et al., 2018). In the context of Tokopedia's TANYA chatbot, elements such as sleek design, localized humor, or TikTok-style summaries can create a sense of modernity that improves satisfaction and supports purchase intention by making the platform appear technologically advanced and culturally relevant.

However, trendiness should not be interpreted as a superficial design attribute. Its influence emerges when modernity signals technological advancement and cultural alignment. In chatbot-mediated e-commerce, elements such as sleek conversational flow, culturally contextualized humor, or dynamic summaries can enhance perceived platform innovation. Consequently, trendiness functions as a symbolic driver within the broader evaluation framework, complementing functional and experiential determinants of satisfaction and behavioral intention.

Taken together, these insights suggest that perceived trendiness strengthens satisfaction and purchase intention by enhancing emotional engagement and reinforcing perceptions of technological sophistication. In AI-driven commerce, staying current is not merely aesthetic – it is strategically linked to user evaluation and competitive positioning.

http://dx.doi.org/10.21511/im.22(3).2026.01

In AI-mediated service environments, communication becomes the primary channel through which users interpret system capability and reliability. Unlike human interactions, where nonverbal cues contribute to meaning, chatbot encounters rely almost entirely on linguistic clarity and conversational coherence. Communication competence, therefore, reflects the extent to which an AI system conveys information clearly, appropriately, and contextually, while maintaining a natural conversational flow. Communication competence refers to a chatbot's perceived ability to communicate clearly, appropriately, and effectively, demonstrated through accurate responses, contextual understanding, and coherent conversational flow (Huang & Rust, 2021).

Within Computer-Mediated Communication theory, effective digital interaction depends on the system's ability to simulate socially appropriate cues in text-based exchanges. When chatbot responses demonstrate contextual understanding, politeness, adaptive phrasing, and coherent dialogue structure, users are more likely to perceive the interaction as credible and professionally managed (Melián-González et al., 2021). In contrast, rigid, repetitive, or templated responses may signal technological limitations, thereby weakening user confidence.

When chatbots deliver clear and empathetic responses, users experience reduced frustration, stronger trust, and a greater sense of being understood – producing higher satisfaction (Grewal et al., 2021). Empirical studies consistently support this relationship, showing that communicatively fluent AI agents enhance emotional satisfaction more than rigid, template-based systems (Prentice et al., 2020; Wang et al., 2023). Communication competence also signals professionalism and technological maturity, strengthening platform credibility and fostering user loyalty (Chung et al., 2020).

In Tokopedia's context, personalized and context-aware replies improve the experience across simple and complex queries. Beyond satisfaction, communication competence reduces uncertainty and enhances the perceived credibility of information, making users more confident in making purchase decisions (Chung et al., 2020). Research shows that effective, fluent communication increases consumer engagement and behavioral intention by reinforcing perceived service quality and trust (Wang et al., 2023). When chatbots communicate clearly, accurately, and persuasively, users feel more assured and more willing to complete a transaction.

Taken together, communication competence functions as a stabilizing mechanism within the broader evaluation framework. It strengthens satisfaction by enhancing clarity and relational comfort, while simultaneously supporting behavioral intention through improved trust and reduced uncertainty. In conversational commerce, therefore, communication is not merely a delivery mechanism but a strategic determinant of user engagement and transactional outcomes.

In AI-mediated commerce, credibility functions as a fundamental cognitive anchor that shapes how users evaluate automated service encounters. When interactions are mediated by algorithmic systems rather than human agents, users rely heavily on cues signaling reliability, competence, and transparency. Credibility, therefore, reflects the extent to which a chatbot is perceived as trustworthy, accurate, and dependable in delivering information and guidance.

Credibility refers to users' perception that a chatbot is trustworthy, competent, and reliable in delivering accurate information. In AI-mediated e-commerce, credibility strongly shapes users' cognitive and emotional evaluations of the service (Garcés-Conejos Blitvich et al., 2019). When chatbot responses are consistent, accurate, and transparent, users experience reduced anxiety and greater confidence, which increases satisfaction (Prentice et al., 2020). Research shows that credible chatbots enhance trust, perceived informativeness, and users' sense of control, thereby lowering perceived risk (Chatterjee et al., 2020; Huang & Benyoucef, 2013).

This aligns with the Elaboration Likelihood Model, in which credible sources foster greater message acceptance. Beyond satisfaction, credibility also drives behavioral intention. In the absence of human assurance, credible chatbots help users feel secure about product quality and transaction safety, increasing the likelihood of purchase (Akter et al., 2022; Almansour & Elkrghli, 2023). For Tokopedia's TANYA, credible communication can reduce uncertainty and strengthen users' willingness to complete purchases.

Beyond influencing satisfaction, credibility directly supports purchase intention by reinforcing perceived transaction safety. In the absence of human reassurance, credible AI systems serve as substitutes for interpersonal trust. When users believe that chatbot responses are accurate and professionally managed, they feel more secure completing purchases. Consequently, credibility acts as a risk-reduction mechanism within AI-driven e-commerce, strengthening both attitudinal and behavioral outcomes.

Taken together, credibility constitutes a relational determinant that stabilizes user evaluation in conversational commerce. It complements functional performance and experiential appeal by providing the trust foundation necessary for satisfaction and transactional commitment.

In digital commerce, customer satisfaction is a pivotal evaluative outcome linking user perceptions to behavioral intention. In AI-mediated environments, satisfaction reflects a comprehensive judgment formed through both cognitive appraisal and affective response. Rather than arising from a single attribute, it emerges from users' overall assessment of whether the chatbot experience meets functional needs, emotional expectations, and relational standards. Customer satisfaction is a central predictor of behavioral intention in both traditional and digital marketing. In AI-enabled e-commerce platforms, such as Tokopedia's chatbot, satisfaction reflects users' emotional and cognitive evaluations of the service experience. When chatbot performance meets or exceeds expectations, users show a higher willingness to proceed with purchases (Anderson & Srinivasan, 2003; Oliver, 1999).

Prior research consistently shows that satisfaction increases purchase intention across digital interfaces, including AI systems (Ashraf et al., 2014; Hsu et al., 2012). Users who are satisfied with chatbot interactions demonstrate greater trust, loyalty, and readiness to transact (Alalwan et al., 2020; Chatterjee et al., 2020). Satisfaction in AI-driven environments is shaped by factors such as usefulness, ease of use, credibility, and interaction quality (Garcés-Conejos Blitvich et al., 2019). Guided by Expectation-Confirmation Theory, satisfaction emerges when users' expectations are confirmed during actual use, thereby strengthening purchase intention (Bhattacherjee, 2001). In Tokopedia's context, seamless and responsive chatbot interactions reduce psychological distance and enhance users' likelihood of completing transactions.

Importantly, satisfaction does more than reflect short-term contentment; it reduces the psychological distance between the user and the platform. When chatbot interactions are seamless and reassuring, users perceive lower risk and greater confidence in transaction outcomes (Chatterjee et al., 2020). As a result, satisfaction serves as both an emotional outcome and a behavioral catalyst, translating multidimensional evaluations into purchase intention.

Taken together, customer satisfaction occupies a central mediating position in AI-driven e-commerce models. It consolidates functional performance, experiential appeal, and relational trust into a unified evaluative judgment that ultimately shapes transactional behaviour.

Taken together, the reviewed literature indicates that user evaluation of AI-powered chatbots in e-commerce is shaped by an integrated constellation of functional, experiential, and relational drivers. Functional attributes such as service quality, information quality, perceived usefulness, and ease of use form the cognitive basis for assessing system performance. Experiential elements, including interaction quality, entertainment, and trendiness, enrich engagement by eliciting affective responses and imbuing it with symbolic value. Relational determinants, particularly communication competence and credibility, reinforce trust and reduce perceived risk in AI-mediated exchanges. These dimensions operate collectively and converge into customer satisfaction as a central evaluative mechanism. Satisfaction subsequently serves as the primary pathway by which multidimensional perceptions translate into purchase intention.

http://dx.doi.org/10.21511/im.22(3).2026.01

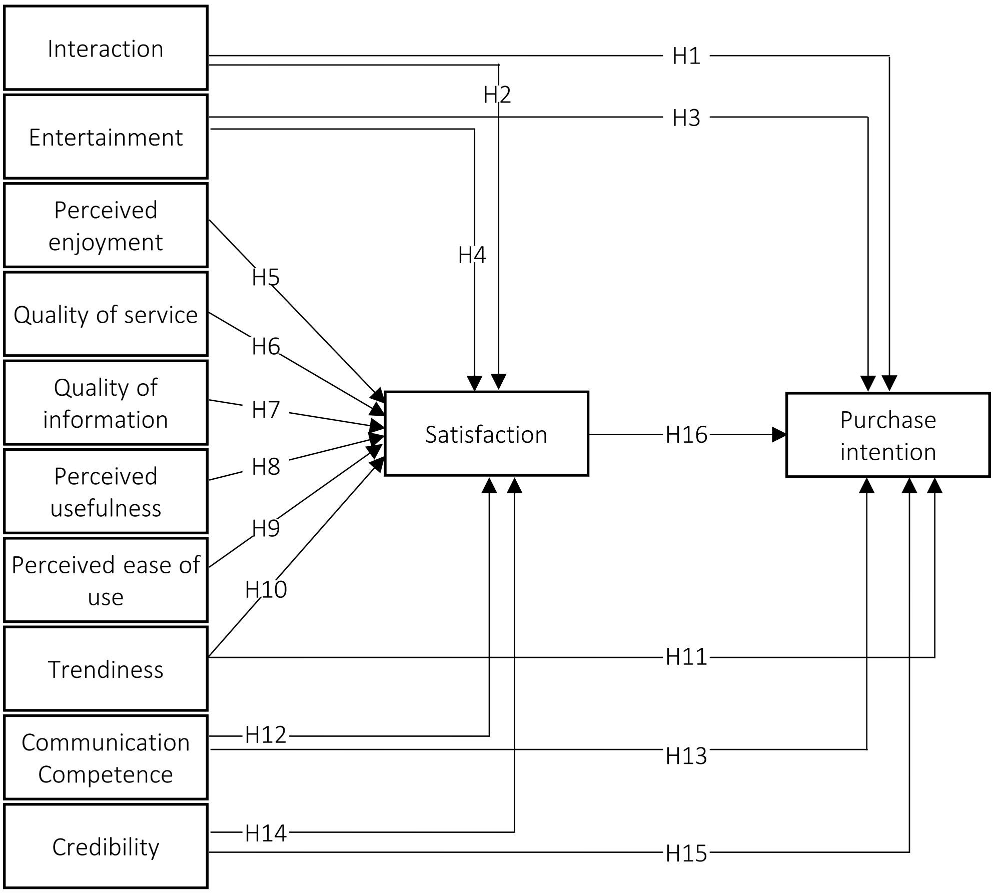

Figure 1. Research model

This study aimed to examine how functional, experiential, and credibility-related attributes of AI-powered chatbots influence customer satisfaction and purchase intention within Indonesia's e-commerce environment.

After conducting a literature review, the hypotheses can be formulated as follows:

H1: Interaction positively influences purchase intention.

H2: Interaction positively influences satisfaction.

H3: Entertainment positively influences purchase intention.

H4: Entertainment positively influences satisfaction.

H5: Perceived enjoyment positively influences satisfaction.

H6: Quality of service positively influences satisfaction

H7: Quality of information positively influences satisfaction.

H8: Perceived usefulness positively influences satisfaction.

H9: Perceived ease of use positively influences user satisfaction.

H10: Trendiness positively influences user satisfaction.

H11: Trendiness positively influences purchase intention.

H12: Communication competence positively influences satisfaction.

H13: Communication competence positively influences purchase intention.

H14: Credibility positively influences satisfaction.

H15: Credibility positively influences purchase intention

H16: Satisfaction positively influences purchase intention.

The literature review has generated 16 hypotheses, leading to the research model shown in Figure 1.

2. METHODOLOGY

This study employed a quantitative research approach to examine how AI-powered chatbot attributes influence customer satisfaction and purchase intention in Indonesia's e-commerce environment. The proposed model integrates three categories of determinants: functional attributes (service quality, information quality, perceived usefulness, and perceived ease of use), experiential attributes (interaction quality, entertainment, perceived enjoyment, and trendiness), and credibility-related attributes (communication competence and credibility). Customer satisfaction was positioned as a mediating variable linking these attributes to purchase intention. The conceptual framework builds on established theories in technology adoption and digital service interaction, including the Technology Acceptance Model (TAM), the Stimulus–Organism–Response (SOR) framework, and service quality theory (Gursoy et al., 2019).

Measurement items were adapted from established scales: trust and personalization (Prentice et al., 2020), perceived convenience (Collier & Kimes, 2013), service quality (Chung et al., 2020), perceived sacrifice (Parasuraman et al., 1988), AI familiarity (Chen et al., 2023), and customer experience (Lemon & Verhoef, 2016). All items used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A pilot test with 30 respondents was conducted to validate the clarity and reliability of the items before they were distributed on a large scale.

To collect empirical data, a structured online questionnaire was distributed to e-commerce consumers in four urban centers within Yogyakarta and Central Java: Yogyakarta City, Surakarta, Magelang, and Semarang. These cities represent growing digital ecosystems with increasing chatbot usage in platforms like Shopee and Tokopedia (Lengkong et al., 2021). A purposive sampling technique was applied. Respondents were required to have interacted with a Tokopedia chatbot. Have done so within the previous six months. A minimum target sample of 250 respondents was determined based on PLS-SEM estimation requirements. After screening for incomplete responses, patterned answers, and extreme response times, only valid questionnaires were retained for analysis.

The study targeted a minimum of 250 valid responses, consistent with guidelines for Partial Least Squares Structural Equation Modeling (PLS-SEM), where sample sizes should be 10 times the largest number of structural paths pointing at a construct (Sarstedt et al., 2021). Data were analyzed using SmartPLS 4 software. The model assessment included outer loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for evaluating reliability and convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio. Path coefficients were tested using bootstrapping (n = 5,000 subsamples) to evaluate hypothesis significance (Sarstedt et al., 2021, 2022). The analysis followed a two-step approach. First, the measurement model was evaluated by assessing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Second, the structural model was assessed by examining path coefficients, explained variance (R^2), and predictive relevance. Hypotheses were tested using bootstrapping with 5,000 resamples to determine statistical significance. Mediation effects were examined through indirect path analysis, while the moderation effects of AI familiarity were tested using interaction terms within the PLS framework.

To minimize common method bias, procedural remedies were implemented, including assurances of anonymity, the separation of predictor and criterion constructs in the questionnaire, and varied item wording. Statistically, Harman's single-factor test indicated that no single factor accounted for the majority of variance. Additionally, full collin-

http://dx.doi.org/10.21511/im.22(3).2026.01

earity Variance Inflation Factors (VIF) were examined and found to be below the recommended threshold, suggesting that common method bias was unlikely to threaten the results. Non-response bias was assessed by comparing early and late respondents using independent sample t-tests. No significant differences were observed, indicating that non-response bias was not a serious concern.

Participation in the study was voluntary. Respondents were informed about the purpose of the research and assured that their responses would remain anonymous and confidential. No personally identifiable information was collected.

3. RESULTS AND DISCUSSION

The outer model results, presented in Table 1, reveal that all indicator loadings exceed the minimum acceptable threshold of 0.70, confirming excellent indicator reliability across constructs. This implies that each manifest variable contributes meaningfully to measuring its corresponding latent variable. These results validate that the constructs have been operationalized using robust and reflective indicators that meet the standards recommended by (Hair et al., 2019). Such high loadings enhance confidence that the measurement model adequately captures the theoretical constructs under investigation, particularly in the context of AI-driven chatbot usage in e-commerce.

In Table 2, internal consistency and convergent validity are assessed using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). All Cronbach's Alpha values are above 0.70, indicating satisfactory reliability, while CR values exceed 0.80 for all constructs, indicating high internal consistency. Additionally, all AVE values are above the recommended threshold of 0.50, confirming that each latent variable explains more than half the variance of its indicators. These findings affirm the convergent validity of the constructs, meaning that the items intended to measure a construct indeed share a high proportion of variance.

Table 1. Outer loading

	COMPET	CREDIB	CUSAT	ENTER	INTER	PE	PEOU	PU	PURINT	QUAL INFO	QUAL SERV	TREND
COMPET1	0.974											
COMPET2	0.963											
COMPET3	0.984											
CREDIB1		0.982										
CREDIB2		0.966										
CREDIB3		0.960										
CREDIB4		0.973										
CUSAT1			0.981									
CUSAT2			0.958									
CUSAT3			0.974									
CUSAT4			0.946									
CUSAT5			0.975									
CUSAT6			0.953									
ENTER1				0.966								
ENTER2				0.969								
ENTER3				0.977								
ENTER4				0.976								
INTER1					0.919							
INTER2					0.944							
INTER3					0.960							
INTER4					0.941							
PE1						0.987						
PE2						0.987						
PE3						0.976						
PE4						0.978						
PEOUI1							0.959					

Table 1 (cont.). Outer loading

	COMPET	CREDIB	CUSAT	ENTER	INTER	PE	PEOU	PU	PURINT	QUAL INFO	QUAL SERV	TREND
PEOUI2							0.959					
PEOUI3							0.980					
PU1								0.964				
PU2								0.974				
PU3								0.951				
PU4								0.956				
PURINT1									0.972			
PURINT2									0.975			
PURINT3									0.968			
PURINT4									0.953			
PURINT5									0.982			
QUALINFO1										0.990		
QUALINFO2										0.985		
QUALINFO3										0.991		
QUALINFO4										0.984		
QUALSERV1											0.990	
QUALSERV2											0.980	
QUALSERV3											0.987	
TREND1												0.957
TREND2												0.979
TREND3												0.972
TREND4												0.976

Notes: COMPET: Communication competence; CREDIB: Credibility; CUSAT: Customer Satisfaction; ENTER: Entertainment; INTER: Interaction; PE: Perceived Enjoyment; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PURINT: Purchase Intention; QUALINFO: Quality of Information; QUALSERV: Quality of Service; TREND: Trendiness.

Table 2. Measurement model reliability and validity

Variables	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
COMPET	0.973	0.982	0.948
CREDIB	0.979	0.985	0.941
CUSAT	0.985	0.988	0.931
ENTER	0.981	0.986	0.945
INTER	0.957	0.969	0.885
PE	0.988	0.991	0.965
PEOU	0.964	0.977	0.933
PU	0.973	0.980	0.924
PURINT	0.984	0.988	0.941
QUALINFO	0.991	0.994	0.975
QUALSERV	0.986	0.990	0.972
TREND	0.980	0.985	0.943

Discriminant validity was evaluated to confirm that each construct is empirically distinct from the others in the model. Table 3 presents the cross-loading values of all measurement items on their respective constructs, in accordance with the Fornell-Larcker criterion. For discriminant validity to be established, an indicator's loading on its assigned construct should be higher than its loadings on any other construct. The results indicate that all items exhibit their highest loading on the intended construct. For example, the item COMPET1 loads more strongly on COMPET (0.988) than on any other constructs, such as CREDIB (0.937) or CUSAT (0.962). Similarly, PE2 shows a strong loading of 0.991 on PE compared to other constructs, such as CUSAT (0.948) or QUALINFO (0.929). These patterns are consistently observed across all constructs and items in the model.

Furthermore, constructs that are conceptually related – such as QUALSERV and QUALINFO, or PEOU and PU – demonstrate high intercorrelations, yet discriminant validity is still maintained as item loadings are significantly higher on their respective latent variables than on these related constructs. This ensures that while the constructs may be theoretically interlinked, they remain statistically distinct.

Discriminant validity was first tested using the Fornell-Larcker criterion, as shown in Table 4. The square root of AVE for each construct is greater

http://dx.doi.org/10.21511/im.22(3).2026.01

Table 3. Discriminant validity

	COMPET	CREDIB	CUSAT	ENTER	INTER	PE	PEOU	PU	PURINT	QUALINFO	QUALSERV	TREND
COMPET1	0.988	0.937	0.962	0.945	0.882	0.965	0.897	0.890	0.930	0.919	0.937	0.950
COMPET3	0.988	0.941	0.957	0.935	0.888	0.957	0.911	0.937	0.961	0.946	0.959	0.982
CREDIB2	0.902	0.977	0.878	0.873	0.931	0.907	0.973	0.883	0.932	0.955	0.921	0.911
CREDIB4	0.955	0.979	0.931	0.934	0.920	0.964	0.932	0.893	0.929	0.951	0.948	0.936
CUSAT3	0.951	0.905	0.982	0.928	0.854	0.924	0.897	0.938	0.946	0.914	0.959	0.957
CUSAT4	0.933	0.890	0.973	0.957	0.843	0.928	0.862	0.888	0.893	0.868	0.904	0.918
CUSAT5	0.969	0.924	0.984	0.928	0.866	0.944	0.900	0.898	0.945	0.912	0.956	0.955
ENTER1	0.926	0.903	0.932	0.987	0.878	0.951	0.867	0.925	0.887	0.880	0.885	0.928
ENTER3	0.952	0.922	0.956	0.987	0.865	0.956	0.872	0.939	0.908	0.899	0.909	0.963
INTER1	0.838	0.887	0.810	0.845	0.959	0.884	0.877	0.829	0.826	0.856	0.829	0.835
INTER4	0.884	0.933	0.866	0.854	0.966	0.901	0.940	0.862	0.912	0.924	0.910	0.884
PE1	0.963	0.954	0.940	0.947	0.921	0.991	0.917	0.919	0.944	0.931	0.937	0.947
PE2	0.970	0.952	0.948	0.956	0.908	0.991	0.911	0.929	0.945	0.929	0.938	0.961
PE4	0.945	0.927	0.927	0.958	0.917	0.979	0.893	0.932	0.904	0.904	0.904	0.946
PEOU1	0.878	0.950	0.861	0.855	0.933	0.894	0.979	0.867	0.906	0.926	0.903	0.883
PEOU3	0.915	0.959	0.913	0.872	0.921	0.909	0.982	0.891	0.959	0.971	0.964	0.918
PU2	0.927	0.909	0.929	0.945	0.870	0.937	0.895	0.986	0.927	0.920	0.921	0.961
PU4	0.894	0.882	0.898	0.916	0.862	0.914	0.873	0.985	0.893	0.886	0.901	0.921
PURINT1	0.934	0.944	0.929	0.890	0.902	0.923	0.950	0.901	0.989	0.962	0.955	0.944
PURINT2	0.938	0.941	0.923	0.896	0.897	0.932	0.940	0.907	0.991	0.950	0.942	0.951
PURINT5	0.965	0.936	0.956	0.911	0.884	0.943	0.931	0.929	0.985	0.952	0.975	0.958
QUALINFO1	0.944	0.970	0.915	0.898	0.922	0.933	0.961	0.917	0.966	0.994	0.963	0.946
QUALINFO3	0.932	0.966	0.907	0.893	0.919	0.923	0.962	0.904	0.954	0.994	0.952	0.934
QUALSERV1	0.941	0.943	0.942	0.886	0.896	0.920	0.940	0.897	0.961	0.951	0.990	0.921
QUALSERV2	0.966	0.925	0.964	0.916	0.869	0.937	0,916	0.937	0.956	0.933	0.980	0.956
QUALSERV3	0.931	0.958	0.931	0.886	0.912	0.920	0.964	0.899	0.948	0.965	0.987	0.915
TREND2	0.958	0.933	0.925	0.918	0.892	0.945	0.924	0.939	0.967	0.945	0.931	0.983
TREND3	0.964	0.925	0.969	0.965	0.865	0.951	0.882	0.939	0.925	0.915	0.926	0.983

than the inter-construct correlations, thereby meeting the criterion for discriminant validity (Fornell & Larcker, 1981). This confirms that each construct is empirically distinct from the others.

Complementing this, Table 5 reports the HTMT (Heterotrait-Monotrait) ratios, which further strengthen the evidence for discriminant validity. All HTMT values are below the most conservative threshold of 0.85, ensuring that none of the constructs conceptually overlap. Together, the Fornell-Larcker and HTMT analyses confirm the robustness and separability of constructs within the measurement model.

Table 4. Fornell-Larcker criterion

	COMPET	CREDIB	CUSAT	ENTER	INTER	PE	PEOU	PU	PURINT	QUALINFO	QUALSERV	TREND
COMPET	0.988											
CREDIB	0.950	0.978										
CUSAT	0.971	0.925	0.980									
ENTER	0.951	0.924	0.957	0.987								
INTER	0.895	0.946	0.872	0.883	0.962							
PE	0.972	0.957	0.951	0.966	0.928	0.987						
PEOU	0.915	0.974	0.905	0.881	0.945	0.919	0.980					
PU	0.924	0.909	0.927	0.944	0.879	0.939	0.897	0.986				
PURINT	0.957	0.952	0.948	0.910	0.905	0.944	0.952	0.923	0.988			
QUALINFO	0.944	0.974	0.917	0.901	0.926	0.934	0.968	0.916	0.966	0.994		
QUALSERV	0.960	0.956	0.959	0.909	0.905	0.939	0.953	0.924	0.969	0.963	0.986	
TREND	0.977	0.945	0.963	0.958	0.894	0.964	0.919	0.955	0.962	0.946	0.944	0.983

Table 5. HTMT ratios

	COMPET	CREDIB	CUSAT	ENTER	INTER	PE	PEOU	PU	PURINT	QUALINFO	QUALSERV	TREND
COMPET	0.778											
CREDIB	0.750	0.778										
CUSAT	0.771	0.725	0.880									
ENTER	0.651	0.624	0.757	0.587								
INTER	0.795	0.546	0.672	0.883	0.862							
PE	0.772	0.657	0.751	0.766	0.728	0.887						
PEOU	0.615	0.774	0.705	0.871	0.745	0.819	0,880					
PU	0.724	0.509	0.727	0.744	0.879	0.839	0,827	0.786				
PURINT	0.657	0.752	0.848	0.810	0.705	0.744	0,752	0.823	0.788			
QUALINFO	0.744	0.674	0.817	0.701	0.826	0.734	0,768	0.716	0.766	0.894		
QUALSERV	0.660	0.756	0.859	0.809	0.805	0.739	0,653	0.824	0.769	0.863	0.786	
TREND	0.677	0.845	0.763	0.758	0.894	0.664	0,819	0.755	0.862	0.746	0.744	0.883

The coefficient of determination (R^2) values shown in Table 6 provide insight into the model's explanatory power. The R^2 value for purchase intention is 0.958, which falls in the moderate-to-substantial range, indicating that over 64% of the variance in purchase intention is explained by the independent variables. Satisfaction, trust, and perceived usefulness also yield strong R^2 values, suggesting that the model has good predictive ability across key endogenous constructs. This indicates the model's potential for practical implementation in strategic marketing decision-making related to AI chatbot integration.

The R-square (R^2) values in Table 6 indicate the proportion of variance in the endogenous (dependent) variables that can be explained by the exogenous (independent) variables in the model. CUSAT (customer satisfaction) has an R^2 value of 0.978, meaning that 97.8% of the variation in customer satisfaction is explained by the antecedent variables in the model (e.g., perceived ease of use, perceived enjoyment, trendiness, credibility, etc.). PURINT (purchase intention) has an R^2 value of 0.958, implying that 95.8% of the variation in consumers' intention to purchase is explained by predictors including satisfaction and other direct paths from factors like trust and emotional engagement. Both R^2 values are extremely high, indicating that the structural model has excellent explanatory power, far exceeding the conventional threshold of 0.67 for substantial models in behavioral science (Chin & Marcoulides, 1998).

Table 6. R-square

Endogenous construct	R-square	R^2 adjusted
CUSAT	0.978	0.977
PURINT	0.958	0.956

Table 7 shows that both Q^2 values far exceed 0.35, indicating extremely strong predictive relevance of the model for both customer satisfaction and purchase intention. This suggests that the independent variables in the model (such as perceived enjoyment, interaction, credibility, etc.) have high explanatory power and are effective in predicting the target variables.

Table 7. Q-square

Endogenous construct	Q-square
CUSAT	0.973
PURINT	0.951

The results presented in Table 8 demonstrate that all sixteen proposed hypotheses (H1–H16) are statistically supported, as indicated by t-values exceeding the critical value of 1.96 and p-values below the 0.05 significance threshold, confirming the robustness of the proposed model. These findings offer compelling evidence regarding the direct and indirect relationships among the studied constructs – namely interaction, entertainment, perceived enjoyment, quality of service, perceived ease of use, trendiness, communication competence, credibility, satisfaction, and purchase intention.

Specifically, interaction (INTER) significantly influences both purchase intention (PURINT) (*H1*: t = 2.657, p = 0.008) and satisfaction (CUSAT) (*H2*: t = 1.997, p = 0.002), highlighting the critical role of interactive experiences in fostering both positive attitudes and behavioral intentions. Similarly, entertainment (ENTER) has a strong positive impact on both purchase intention (*H3*: t = 5.718, p = 0.000) and satisfaction (*H4*: t = 5.733, p = 0.000),

http://dx.doi.org/10.21511/im.22(3).2026.01

underlining the entertainment value of chatbot interactions as a key driver of user outcomes.

Perceived enjoyment (PE) was found to significantly affect satisfaction (*H5*: t = 2.705, p = 0.001), reinforcing the notion that emotionally gratifying experiences enhance satisfaction levels. Furthermore, service quality (QUALSERV) (*H6*: t = 6.847, p = 0.000) and information quality (QUALINFO) (*H7*: t = 2.952, p = 0.003) also have significant positive effects on satisfaction, confirming previous findings that system and content quality are essential to user fulfillment.

Besides, perceived usefulness (PU) (*H8*: t = 3.100, p = 0.002) and perceived ease of use (PEOU) (*H9*: t = 2.509, p = 0.012) also contribute significantly to satisfaction, validating key tenets of the Technology Acceptance Model (TAM) within the context of chatbot services. Trendiness (TREND) affects both satisfaction (*H10*: t = 2.578, p = 0.010) and purchase intention (*H11*: t = 5.286, p = 0.000), suggesting that cutting-edge and fashionable interfaces enhance user engagement and conversion potential.

Additionally, communication competence (COMPET) shows significant effects on both satisfaction (*H12*: t = 1.998, p = 0.003) and purchase intention (*H13*: t = 2.111, p = 0.001), indicating that the chatbot's ability to deliver clear, concise, and relevant communication plays a critical role in shaping user outcomes. Credibility (CREDIB) also positively influences satisfaction (*H14*: t = 2.751, p = 0.006) and purchase intention (*H15*: t = 3.889, p = 0.000), emphasizing the importance of trustworthiness in digital interactions.

Finally, satisfaction (CUSAT) itself significantly predicts purchase intention (*H16*: t = 3.185, p = 0.002), providing strong evidence for its mediating role in the relationship between various antecedents and the user's behavioral intention. This result reinforces satisfaction as a central construct in driving purchase decisions, thereby validating its inclusion as a key mediator in the proposed model.

The findings provide several important insights. First, service quality emerged as the strongest predictor of satisfaction. This indicates that responsiveness, reliability, and accuracy remain the foundational determinants of user evaluation, even in AI-mediated environments. While prior research has consistently emphasized service quality as critical in digital services (Almansour & Elkrghli, 2023), our findings suggest that its role becomes even more pronounced in chatbot-based interactions, where human support is replaced by automated systems. This reinforces the argument that AI systems must meet or exceed human service standards to sustain user confidence.

Second, entertainment and trendiness significantly influenced both satisfaction and purchase intention. Unlike earlier e-commerce research

Table 8. Hypotheses testing

Hypothesis	Path coefficient	t-statistics	p-values	Results
H1	INTER → PURINT	2.657	0.008	Accepted
H2	INTER → CUSAT	1.997	0.002	Accepted
H3	ENTER → PURINT	5.718	0.000	Accepted
H4	ENTER → CUSAT	5.733	0.000	Accepted
H5	PE → CUSAT	2.705	0.001	Accepted
H6	QUALSERV → CUSAT	6.847	0.000	Accepted
H7	QUALINFO → CUSAT	2.952	0.003	Accepted
H8	PU → CUSAT	3.100	0.002	Accepted
H9	PEOU → CUSAT	2.509	0.012	Accepted
H10	TREND → CUSAT	2.578	0.010	Accepted
H11	TREND → PURINT	5.286	0.000	Accepted
H12	COMPET → CUSAT	1.998	0.003	Accepted
H13	COMPET → PURINT	2.111	0.001	Accepted
H14	CREDIB → CUSAT	2.751	0.006	Accepted
H15	CREDIB → PURINT	3.889	0.000	Accepted
H16	CUSAT → PURINT	3.185	0.002	Accepted

that positioned hedonic attributes as complementary to functional value, our results indicate that affective and aesthetic dimensions are not peripheral but central drivers of behavioral intention. This finding extends previous studies (Ashfaq et al., 2020; Huang et al., 2024) by demonstrating that, in a Gen-Z-dominated market such as Indonesia, emotional engagement and modern interface design may rival functional efficiency in shaping purchase decisions. Compared to traditional TAM-based models, which prioritize usefulness and ease of use, our model suggests that experiential appeal has become equally influential in AI-driven contexts.

Third, perceived usefulness and perceived ease of use significantly enhanced satisfaction, confirming the continued relevance of TAM in explaining AI adoption. However, unlike early TAM studies where usefulness was typically the dominant predictor of behavioral intention, in this study its effect was comparatively balanced with entertainment and trendiness. This suggests a contextual shift: in conversational commerce environments, user experience is multidimensional, blending efficiency with emotional gratification.

Fourth, credibility and communication competence significantly affected both satisfaction and purchase intention. This finding aligns with previous chatbot research emphasizing trust formation in AI interactions, yet our results highlight that communication fluency and contextual clarity are not merely trust antecedents – they directly influence transactional intention. Compared with earlier studies that treated credibility primarily as a mediator through trust, our findings suggest a more direct behavioral pathway in e-commerce chatbot settings.

The exceptionally high explanatory power of the model (R^2 values for satisfaction and purchase intention) indicates that combining technological, experiential, and symbolic constructs provides a comprehensive understanding of user behavior. However, such high R^2 values may also reflect contextual homogeneity within the sample urban, digitally active users which could amplify construct interrelationships. Future studies should test the model across more diverse demographic segments to validate its generalizability.

Importantly, satisfaction demonstrated a significant direct effect on purchase intention, confirming its central mediating role. This finding is consistent with expectation-confirmation logic in digital commerce. However, our results extend prior research by showing that satisfaction operates within a broader experiential ecosystem, where design aesthetics and entertainment features are structurally embedded rather than secondary enhancements.

This study contributes to AI and marketing literature in three ways. First, it extends TAM by integrating experiential constructs such as entertainment and trendiness, demonstrating that AI chatbot adoption cannot be fully explained by functional determinants alone. Second, it bridges service quality theory and digital marketing by positioning chatbot interactions as both a service encounter and a brand-experience touchpoint. Third, it highlights the increasing importance of symbolic and aesthetic value in AI-mediated commerce, particularly among younger consumers in emerging markets.

For platform developers and digital marketers, the findings indicate that optimizing chatbot performance alone is insufficient. While technical reliability remains critical, platforms should simultaneously enhance emotional engagement, interface modernity, and conversational personality. Chatbots should be designed not only to solve problems efficiently but also to create enjoyable and socially relevant experiences. Integrating personalization, adaptive responses, and culturally aligned digital cues may strengthen both satisfaction and purchase intention.

CONCLUSION AND FUTURE RESEARCH

This study aimed to examine how functional, experiential, and credibility-related attributes of AI-powered chatbots influence customer satisfaction and purchase intention within Indonesia's e-commerce environment. By testing an integrated structural model, the study sought to clarify which factors most strongly drive behavioral outcomes in conversational commerce.

http://dx.doi.org/10.21511/im.22(3).2026.01

The results demonstrate that chatbot effectiveness is not determined solely by functional performance. While service quality and perceived usefulness remain important foundations, experiential attributes such as entertainment and trendiness, along with credibility and communication competence, substantially shape both satisfaction and purchase intention. Satisfaction, in turn, serves as a crucial mechanism translating user perceptions into transactional intention. These findings indicate that chatbot-driven commerce operates within a multidimensional evaluative process combining efficiency, emotional engagement, and symbolic value.

From these results, it can be concluded that AI chatbots should be conceptualized not merely as automated service tools but as strategic touchpoints within the broader digital customer experience ecosystem. In emerging digital markets, where users are highly responsive to interface aesthetics and interactive engagement, affective and symbolic drivers appear to carry comparable weight to utilitarian benefits. Thus, competitive advantage in AI-mediated commerce depends on harmonizing technical reliability with emotionally resonant design.

Several avenues for future research emerge from this study. First, the model should be validated across different demographic segments and cultural contexts to assess its generalizability. Second, longitudinal research could examine how repeated chatbot interactions influence trust development and long-term loyalty. Third, future studies may incorporate psychological readiness, AI anxiety, or resistance constructs to better capture consumer heterogeneity in AI adoption. Finally, experimental designs comparing human-agent versus AI-agent interactions could further clarify boundary conditions of chatbot effectiveness.

AUTHOR CONTRIBUTIONS

Conceptualization: Muinah Fadhilah, Ratih Kusumawardhani.
Data Curation: Muinah Fadhilah, Ratih Kusumawardhani, Ambar Lukitaningsih.
Formal Analysis: Muinah Fadhilah, Ratih Kusumawardhani, Ambar Lukitaningsih.
Investigation: Muinah Fadhilah, Ratih Kusumawardhani, Ambar Lukitaningsih.
Methodology: Ratih Kusumawardhani, Ambar Lukitaningsih.
Project Administration: Ratih Kusumawardhani.
Supervision: Ratih Kusumawardhani.
Validation: Muinah Fadhilah, Ambar Lukitaningsih.
Visualization: Ambar Lukitaningsih.
Writing- original draft: Muinah Fadhilah, Ratih Kusumawardhani, Ambar Lukitaningsih.
Writing- review & editing: Muinah Fadhilah, Ratih Kusumawardhani, Ambar Lukitaningsih.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support provided by the Ministry of Higher Education, Science, and Technology (KEMENDIKTISAINTEK) of the Republic of Indonesia through the regular fundamental research grant scheme (PFR). This research was funded under the contract number 126/C3/DT.05.00/PL/2025; 0498.02/LL5-INT/AL.04/2025; 012/DPPM.LLDIKTI/PFR/UST/LP2M/K/VI/2025. The findings and opinions expressed in this article are solely the responsibility of the authors and do not necessarily reflect the views of the funding institution.

REFERENCES

1. Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets, 31*(2), 427-445. https://doi.org/10.1007/s12525-020-00414-7
2. Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics. *Annals of Operations Research, 308*(1), 7-39. https://doi.org/10.1007/s10479-020-03620-w
3. Alalwan, A. A., Algharabat, R. S., Baabdullah, A. M., Rana, N. P., Qasem, Z., & Dwivedi, Y. K. (2020). Examining the impact of mobile interactivity on customer engagement in the context of mobile shopping. *Journal of Enterprise Information Management, 33*(3), 627-653. https://doi.org/10.1108/JEIM-07-2019-0194
4. Almansour, B., & Elkrghli, S. (2023). Factors Influencing Customer Satisfaction on E-Banking Services: A Study of Libyan Banks. *International Journal of Technology, Innovation and Management (IJTIM), 3*(1), 34-42. https://doi.org/10.54489/ijtim.v3i1.211
5. Alshammari, S. H., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students' behavioural intention to use ChatGPT. *Scientific Reports, 15*(1), 7169. https://doi.org/10.1038/s41598-025-91634-4
6. Alzahrani, L., & Seth, K. P. (2021). The impact of organizational practices on the information security management performance. *Information (Switzerland), 12*(10). https://doi.org/10.3390/info12100398
7. Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: A contingency framework. *Psychology & Marketing, 20*(2), 123-138. https://doi.org/10.1002/mar.10063
8. Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54,* 101473. https://doi.org/10.1016/J.TELE.2020.101473
9. Ashraf, Abdul R, Thongpapanl, Narongsak (Tek), & Auh, Seigyoung. (2014). The Application of the Technology Acceptance Model under Different Cultural Contexts: The Case of Online Shopping Adoption. *Journal of International Marketing, 22*(3), 68-93. https://doi.org/10.1509/jim.14.0065
10. Belanche, D., Casaló, L. V, & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7), 1411-1430. https://doi.org/10.1108/IMDS-08-2018-0368
11. Beyari, H., & Garamoun, H. (2022). The Effect of Artificial Intelligence on End-User Online Purchasing Decisions: Toward an Integrated Conceptual Framework. *Sustainability (Switzerland), 14*(15). https://doi.org/10.3390/su14159637
12. Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model1. *Management Information Systems Quarterly, 25*(3), 351-370. https://doi.org/10.2307/3250921
13. Brandtzaeg, P. B., & Folstad, A. (2018). Chatbots: changing user needs and motivations. *Interactions, 25*(5), 38-43. https://doi.org/10.1145/3236669
14. Chatterjee, S., Chaudhuri, R., Vrontis, D., & Kadić-Maglajlić, S. (2023). Adoption of AI integrated partner relationship management (AI-PRM) in B2B sales channels: Exploratory study. *Industrial Marketing Management, 109,* 164-173. https://doi.org/10.1016/J.INDMARMAN.2022.12.014
15. Chen, B., Giannikos, C. I., & Lou, J. (2023). Is More Financial Literacy Always Beneficial? An Investigation through a Mediator. *Journal of Risk and Financial Management, 16*(1). https://doi.org/10.3390/jrfm16010053
16. Chen, S., Li, X., Liu, K., & Wang, X. (2023). Chatbot or human? The impact of online customer service on consumers' purchase intentions. *Psychology & Marketing, 40*(11), 2186-2200. https://doi.org/https://doi.org/10.1002/mar.21862
17. Chin, W., & Marcoulides, G. (1998). The Partial Least Squares Approach to Structural Equation Modeling. *Modern Methods for Business Research, 8*. Retrieved from https://www.researchgate.net/publication/311766005_The_Partial_Least_Squares_Approach_to_Structural_Equation_Modeling?__cf_chl_f_tk=NwcXiQRsQW8hKQL2NYDL7Ntp26myHOpP4BYRzPBBj7M-1782902593-1.0.1.1-6DWtaAcYx8BR1LEoy9HeB8asaQl.pIM49GTd_1KR1mM
18. Chowdhury, F. P., Mazmum, M. F. A., & Akter, M. S. (2025). Exploring Factors Influencing Behavioral Intention to Use Chatbot Services in the Banking Industry of Bangladesh. *Bangladesh Journal of MIS, 11*(2). https://doi.org/10.61606/bjmis.v11n2a3
19. Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research, 117,* 587-595. https://doi.org/10.1016/J.JBUSRES.2018.10.004
20. Collier, J. E, & Kimes, S. E. (2013). Only If It Is Convenient: Understanding How Convenience Influences Self-Service Technology Evaluation. *Journal of Service Research, 16*(1), 39-51. https://doi.org/10.1177/1094670512458454
21. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Management Information Systems Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

http://dx.doi.org/10.21511/im.22(3).2026.01

22. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

23. Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems, 19*(4), 9-30. https://doi.org/10.1080/07421222.2003.11045748

24. Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18*(3), 382-388. https://doi.org/10.2307/3150980

25. Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior, 80,* 271-282. https://doi.org/10.1016/j.chb.2017.11.014

26. Garcés-Conejos Blitvich, Fernández-Amaya, L., & Fernández-Amaya, L. (2019). *Technology Mediated Service Encounters*. John Benjamins Publishing Company. https://doi.org/doi:10.1075/pbns.300

27. Ghazali, E. M., Ngiam, E. Y.-L., & Mutum, D. S. (2020). Elucidating the drivers of residential mobility and housing choice behaviour in a suburban township via push–pull–mooring framework. *Journal of Housing and the Built Environment, 35*(2), 633-659. https://doi.org/10.1007/s10901-019-09705-8

28. Grewal, D., Guha, A., Satornino, C. B., & Schweiger, E. B. (2021). Artificial intelligence: The light and the darkness. *Journal of Business Research, 136,* 229-236. https://doi.org/10.1016/J.JBUSRES.2021.07.043

29. Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49,* 157-169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

30. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

31. Haugeland, I. K. F., Følstad, A., Taylor, C., & Alexander, C. (2022). Understanding the user experience of customer service chatbots: An experimental study of chatbot interaction design. *International Journal of Human-Computer Studies, 161,* 102788. https://doi.org/10.1016/J.IJHCS.2022.102788

32. Hsu, C.-L., Chang, K.-C., & Chen, M.-C. (2012). The impact of website quality on customer satisfaction and purchase intention: perceived playfulness and perceived flow as mediators. *Information Systems and E-Business Management, 10*(4), 549-570. https://doi.org/10.1007/s10257-011-0181-5

33. Huang, D., Markovitch, D. G., & Stough, R. A. (2024). Can chatbot customer service match human service agents on customer satisfaction? An investigation in the role of trust. *Journal of Retailing and Consumer Services, 76,* 103600. https://doi.org/10.1016/J.JRETCONSER.2023.103600

34. Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30-50. https://doi.org/10.1007/s11747-020-00749-9

35. Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications, 12*(4), 246-259. https://doi.org/10.1016/j.elerap.2012.12.003

36. Islam, J. U., Rahman, Z., & Hollebeek, L. D. (2018). Consumer engagement in online brand communities: a solicitation of congruity theory. *Internet Research, 28*(1), 23-45. https://doi.org/10.1108/IntR-09-2016-0279

37. Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior. *Computers in Human Behavior, 134,* 107329. https://doi.org/10.1016/J.CHB.2022.107329

38. Lemon, K. N, & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal of Marketing, 80*(6), 69-96. https://doi.org/10.1509/jm.15.0420

39. Lengkong, O., Dawn Tumewu, M., Thelma, N., & Lumintang, T. (2021). Analisis Usability Pada Aplikasi M-Commerce Tokopedia Terhadap Kepuasan Pengguna Menggunakan USE (Usefulness, Satisfaction, Ease of Use) Questionnaire [Usability Analysis of the Tokopedia M-Commerce Application Towards User Satisfaction Using the USE (Usefulness, Satisfaction, Ease of Use) Questionnaire]. *Cogito Smart Journal, 7*(1), 182-192. https://doi.org/10.31154/cogito.v7i1.311.182-192

40. Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937-947. https://doi.org/10.1287/mksc.2019.1192

41. Lynn, N. D., Sourav, A. I., & Setyohadi, D. B. (2020). Increasing User Satisfaction of Mobile Commerce using Usability. *IJACSA (International Journal of Advanced Computer Science and Applications), 11*(8). https://dx.doi.org/10.14569/IJACSA.2020.0110839

42. Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. *Journal of Business Research, 161,* 113838. https://doi.org/10.1016/J.JBUSRES.2023.113838

43. Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

44. Melián-González, S., Gutiérrez-Taño, D., & Bulchand-Gidumal, J. (2021). Predicting the intentions to use chatbots for travel and

tourism. *Current Issues in Tourism, 24*(2), 192-210. https://doi.org/10.1080/13683500.2019.1706457

45. Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing, 36*(5), 489-501. https://doi.org/https://doi.org/10.1002/mar.21192
46. Na, T. K., Lee, S. H., & Yang, J. Y. (2021). Moderating effect of gender on the relationship between technology readiness index and consumers' continuous use intention of self-service restaurant kiosks. *Information (Switzerland), 12*(7). https://doi.org/10.3390/info12070280
47. Oliver, R. L. (1999). Whence Consumer Loyalty? *Journal of Marketing, 63*(4_suppl1), 33-44. https://doi.org/10.1177/00222429990634s105
48. Parasuraman, A. P., Zeithaml, V., & Berry, L. (1988). SERVQUAL A Multiple-item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing, 64,* 12-40. Retrieved from https://www.researchgate.net/publication/200827786_SERVQUAL_A_Multiple-item_Scale_for_Measuring_Consumer_Perceptions_of_Service_Quality
49. 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
50. Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing & Management, 29*(7), 739-756. https://doi.org/10.1080/19368623.2020.1722304
51. Ruggiero, T. E. (2000). Uses and Gratifications Theory in the 21st Century. *Mass Communication and Society, 3*(1), 3-37. https://doi.org/10.1207/S15327825MCS0301_02
52. Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology and Marketing, 39*(5), 1035-1064. https://doi.org/10.1002/mar.21640
53. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 1-47). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-2
54. Thong, J. Y. L., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies, 64*(9), 799-810. https://doi.org/10.1016/j.ijhcs.2006.05.001
55. Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: the mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing, 15*(3), 460-482. https://doi.org/10.1108/JRIM-12-2019-0200
56. Vahdat, Arash, Alizadeh, Ali, Quach, Sara, & Hamelin, Nicolas. (2021). Would you like to shop via mobile app technology? The technology acceptance model, social factors and purchase intention. *Australasian Marketing Journal, 29*(2), 187-197. https://doi.org/10.1016/j.ausmj.2020.01.002
57. van der Heijden, H. (2004). User Acceptance of Hedonic Information Systems1. *Management Information Systems Quarterly, 28*(4), 695-704. https://doi.org/10.2307/25148660
58. Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research, 11*(4), 342-365. https://doi.org/10.1287/isre.11.4.342.11872
59. Wang, L., Tong, C., & Yang, Z. (2023). Linking CIO–CMO Communication and Product Innovation via Virtual Customer Environment Engagement: A Moderated Mediation Study. *British Journal of Management, 34*(1), 259-279. https://doi.org/10.1111/1467-8551.12587
60. Xie, C., Wang, Y., & Cheng, Y. (2024). Does Artificial Intelligence Satisfy You? A Meta-Analysis of User Gratification and User Satisfaction with AI-Powered Chatbots. *International Journal of Human–Computer Interaction, 40*(3), 613-623. https://doi.org/10.1080/10447318.2022.2121458
61. Yun, J., & Park, J. (2022). The Effects of Chatbot Service Recovery With Emotion Words on Customer Satisfaction, Repurchase Intention, and Positive Word-Of-Mouth. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.922503

http://dx.doi.org/10.21511/im.22(3).2026.01