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The Impact of Integrating Artificial Intelligence Tools on Customer Experience in E-Commerce

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Abstract **Original Research Article**

The fast growth of technologies related to artificial intelligence (AI) has significantly changed e-commerce operations and how customers engage in such activities. This report investigates the influence of the adoption of AI tools on customer experience in e-commerce, with a focus on the mediating roles of customer satisfaction and customer loyalty. Based on the concepts of the Unified Theory of Acceptance and Use of Technology and the Expectation Confirmation Model, the research method is quantitative, with data from 206 valid survey responses. Data analysis using Partial Least Squares Structural Equation Modeling tested the hypothesized relationships among the constructs. It was found that AI tools have a significant impact on enhancing customer satisfaction and increasing customer loyalty, ultimately influencing overall customer experience. Partial mediation effects were also confirmed, indicating that the impact of AI tools on experience would primarily go through satisfaction and loyalty. This study contributes theoretically by extending prior literature in explaining experiential outcomes driven by AI. It also provides managerial implications for developing AI systems in e-commerce platforms, where efficiency improvements should be designed to foster emotional connections and lead to long-term customer loyalty.

Keywords: artificial intelligence tools, AI, UTAUT, ECM, customer satisfaction, customer loyalty, customer experience, and PLS-SEM.

1. Introduction

The swift advancement of artificial intelligence (AI) technologies has significantly transformed the digital environment and reshaped the manner in which they interact with customers (M. Joshi, 2024). Grewal et al. (2024) emphasize that "the adoption of AI is now imperative, rather than optional, for marketing and customer experience within the digital economy." AI tools, software systems that utilize algorithms, machine learning, and data analytics to execute tasks that necessitate human-like cognitive functions, have emerged as pivotal to this metamorphosis (Rashid & Kausik, 2024). AI tools as chatbots, recommendation systems, and virtual assistants, facilitate expedited responses, tailored services, and enhanced user experiences. As reported by Daniela Coppola (2025), the utilization of AI tools enables the formulation of highly personalized interactions that elevate customer satisfaction, loyalty, and overall experiences.

E-commerce has evolved into one of the most dynamic and competitive domains within the digital economy, wherein customer experience constitutes a fundamental factor influencing long-term success

(Deng, 2022). E-commerce, or electronic commerce, characterized by the transaction of goods and services via digital platforms, including websites, mobile applications, and social media, increasingly depends on AI to refine operations and enhance customer experiences (McKinsey Insights, 2025). The integration of AI technologies empowers e-commerce platforms to deliver real-time assistance, personalized suggestions, and fluid shopping experiences, all of which contribute to elevated levels of customer satisfaction, loyalty, and overall experience (Gao et al., 2025). Nonetheless, notwithstanding its pervasive adoption, the genuine implications of AI tools on customer experience within e-commerce remain a multifaceted and developing field of inquiry, necessitating further investigation.

Despite the extensive research about AI integration in e-commerce, notable gaps remain in understanding its broader impact on customer experience. The majority of existing studies concentrate on particular applications such as personalization, recommendation systems, or customer satisfaction, rather than examining how AI influences the holistic customer experience. Although Mariani & Borghi (2021) and Pizzi et al. (2021) underscore AI's contribution to enhancing efficiency and personalization, they provide limited perspectives on its impacts on the emotional and interactive facets of customer experience. Furthermore, conventional marketing literature (e.g., Homburg et al., 2017; Lemon & Verhoef, 2016) perceives customer experience as a precursor to satisfaction and loyalty, while emerging investigations (e.g., Grewal et al., 2023; Huang & Rust, 2018) propose a reciprocal relationship in AI-driven environments, where satisfaction and loyalty can concurrently bolster customer experience. The research gaps delineated are (1) the deficiency in understanding how AI tools integration influences the overall customer experience in e-commerce and (2) the limited exploration of the triadic interaction among customer experience, loyalty, and satisfaction within AI-driven e-commerce frameworks.

In response to these gaps, this study is guided by two main research objectives. Accordingly, the objectives of this research are (1) to investigate the impact of AI tools integration on the overall customer experience within e-commerce and (2) to examine the mediating role of customer satisfaction and loyalty in the relationship between AI tools and customer experience in e-commerce contexts. Corresponding to these objectives, the study is structured around the following research questions: (1) Does the integration of AI tools influence the overall customer experience in e-commerce? (2) Do customer satisfaction and customer loyalty mediate the relationship between AI tools integration and customer experience in e-commerce?

This report proposes a significant theoretical advancement by synthesizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as articulated by Venkatesh et al. (2003) alongside the Expectation-Confirmation Model (ECM), conceptualized by Bhattacherjee (2001), thereby constructing a comprehensive framework elucidating the impact of AI tools on customer satisfaction, loyalty, and experience within e-commerce. By combining these theoretical perspectives, the research offers a comprehensive comprehension of both the initial adoption and the enduring engagement processes that shape customer experiences when interfacing with AI-driven systems (Singh, 2020). This theoretical integration further enriches the conceptual development of the customer experience by positioning satisfaction and loyalty as mediating variables linking technology acceptance (UTAUT) with ongoing experiential outcomes (ECM). Moreover, this study reconciles two theoretical frameworks and elevates the conceptual understanding of how AI technologies co-create value and affect long-term customer relationships in the digital marketplace. It underscores the intricate relationships among customer expectations, emotional satisfaction, and loyalty, while laying the groundwork for the development of a human-AI interaction theory beyond the confines of e-commerce.

Otherwise, AI, intelligent technology designed to communicate similarly to a human, is steadily replacing professional work in e-commerce, especially in the field of customer service (Daniela

Coppola - Statista, 2025). Thus, this report yields significant managerial insights for e-commerce enterprises aiming to augment customer satisfaction, loyalty, and overall experience via the integration of AI technologies. The research highlights that successful AI incorporation must not solely prioritize automation and operational efficiency but should also cultivate meaningful, trust-based customer relationships. Organizations can operationalize these insights by devising AI-driven solutions that tailor services, guarantee transparency in decision-making processes, and achieve a judicious equilibrium between technological efficiency and human interaction. The findings underscore the necessity of establishing ethical and transparent AI practices, employing data analytics to assess satisfaction and engagement levels, and aligning AI strategies with overarching customer relationship objectives.

2. Literature Review and Hypothesis

2.1. Theoretical Model

This study adopts an integrated theoretical framework by synthesizing the UTAUT and ECM to bridge existing gaps in understanding how the usage of AI tools affects customer experience in e-commerce. UTAUT elucidates the manner in which customers' pre-adoption perceptions are shaped, accentuating the engagement and interactions with AI-driven services and innovative technologies (H. Joshi, 2025). In the meantime, ECM documents post-adoption AI-experiences, emphasizing the significance of expected confirmation and perceived usefulness in generating satisfaction, loyalty, and prolonged experience (Gao et al., 2025). Thus, by bridging the gap between initial adoption and long-term usage, this research develops a unified model that clarifies how the integration of AI tools into customer experience through e-commerce.

2.1.1. The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT), formulated by Venkatesh et al. (2003), is a preeminent framework for scrutinizing technology adoption by investigating key factors that impact customer behaviors prior to direct experience with the technology. Within the framework of AI-driven e-commerce, UTAUT offers critical insights into the mechanisms by which customers construct initial beliefs and expectations regarding AI tools, thereby elucidating the perceived ease of use and convenience relating to AI-enhanced purchasing experiences, which elucidates the extent to which customers trust that they enable effective interaction with AI technology-powered systems. (Liu et al., 2025). Similarly, Murrar et al. (2025) emphasize that people who believe AI-tool-powered solutions are simple and engaging to use are more likely to take action on them. Therefore, UTAUT serves as a significant framework for comprehending the evaluative processes customers experience regarding AI-based services prior to complete immersion in them.

By integrating the UTAUT framework at the pre-adoption stage, this study seeks to uncover the psychological and functional mechanisms underlying customer acceptance of AI in e-commerce (Rahimi & Oh, 2024). Recognizing these anticipations facilitates the development of AI solutions that correspond with customer demands and forecast early adoption behaviors and willingness to engage with technologies such as chatbots, recommendation engines, and virtual assistants, thereby enhancing the overall experience in e-commerce (S. Ahmed & Aziz, 2025). The assimilation of UTAUT theory into the design of AI-driven customer service fortifies long-term customer loyalty and satisfaction and exerts a direct influence on customer experience, as seamless and intuitive interactions foster perceptions of efficiency and personalization.

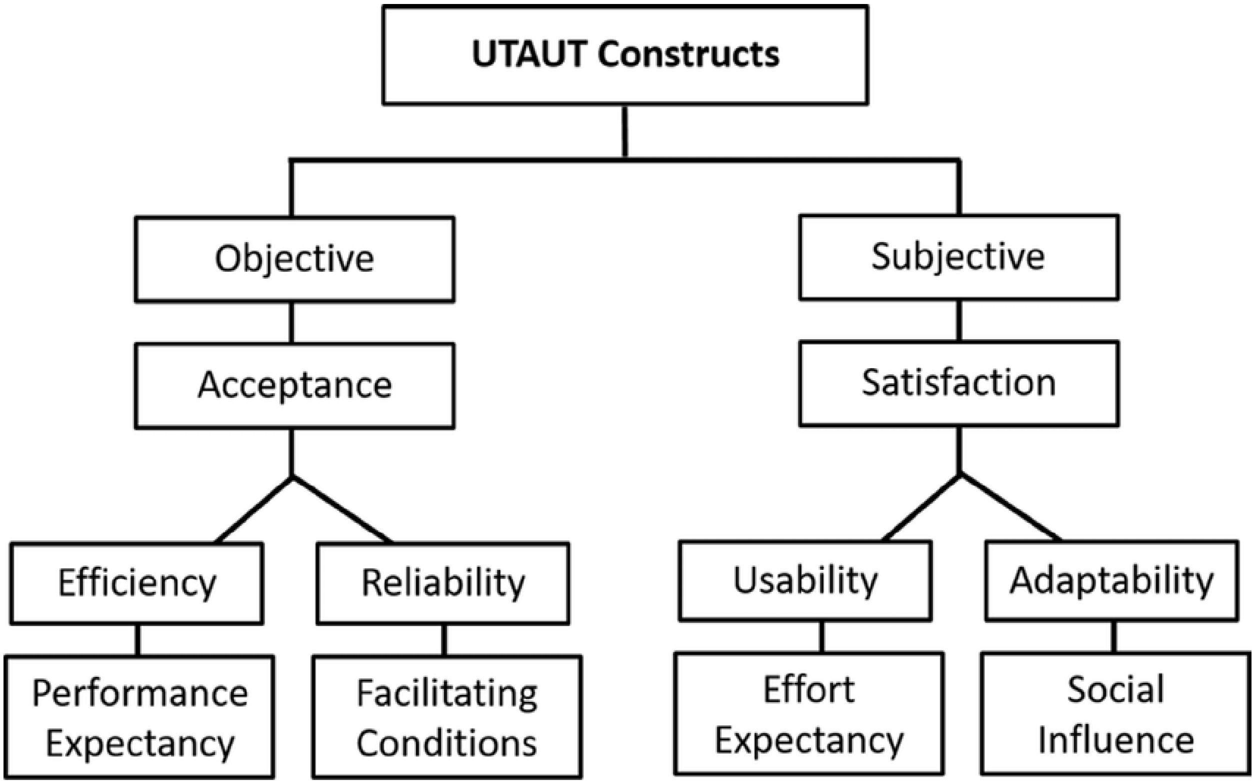

Figure 1. The UTAUT concept

Source: (Momani, 2020)

2.1.2. The Expectation Confirmation Model

Expectation Confirmation Model (ECM), initially posited by Oliver (1980), investigates the way customers' expectations and their subsequent confirmation or disconfirmation impact perceived product performance and overall satisfaction, which subsequently shapes repurchase intentions. Essentially, ECM elucidates post-adoption behavior by concentrating on how users assess a product or service subsequent to initial usage, particularly with respect to whether the actual performance aligns with, surpasses, or falls short of antecedent expectations (Wu & Mvondo, 2025). Within the context of AI-powered e-commerce, ECM clarifies how customers' post-adoption experiences with AI-driven services shape their satisfaction and ongoing utilization (Brown et al., 2014).

In the domain of AI tools in e-commerce, ECM elucidates the evolution of customer satisfaction and loyalty as customers engage with the authentic capabilities of AI tool systems. When the AI tools consistently meet or surpass customer expectations, satisfaction levels rise, thereby fortifying customer loyalty and fostering long-term experiences (Fu et al., 2018). Conversely, unmet expectations may precipitate dissatisfaction and disengagement. Consequently, ECM underscores the essential role of experience-based evaluation in cultivating sustainable relationships between customers and AI technologies, highlighting that ongoing satisfaction is paramount for promoting positive customer experiences and sustaining loyalty in the e-commerce landscape.

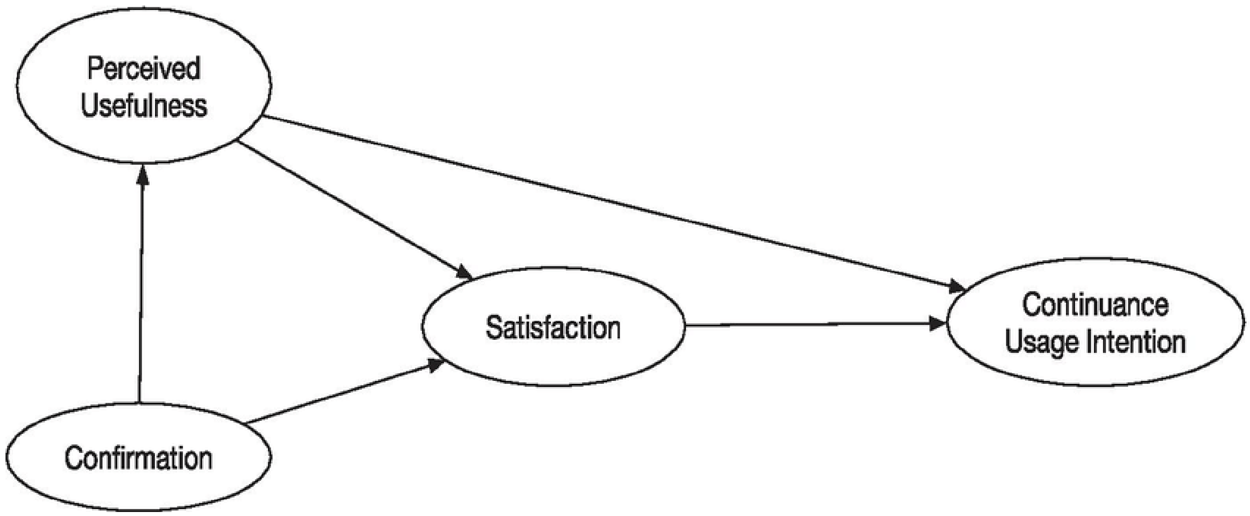

Figure 2. The ECM concept

Source: (Hossain & Quaddus, 2011)

2.2. Second-order Construct

According to research by Nguyen et al. (2023), customers' perceptions of worth reflect a two-way conversation between the two parties. In this study, Customer Experience (CUE) is conceptualized as a second-order reflective construct that captures the multifaceted nature of customers' interactions with AI tools in e-commerce environments. By treating each value dimension as an essential element within a hierarchical second-order model, the study gains a deeper understanding that CUE is not a single, uniform perception but a composite of several interrelated dimensions that together represent the overall experiential value derived from using AI-enabled services (Chau et al., 2025). Specifically, CUE comprises three distinct first-order value dimensions-sensory, emotional, and social experiences reflecting a characteristic aspect of how customers perceive and engage with AI tool-driven customer service systems (Tri-Quan Dang et al., 2025). This second-order structure is justified both theoretically and empirically. Theoretically, it aligns with prior conceptualizations of CUE as a multidimensional phenomenon encompassing cognitive, emotional, and behavioral components (Klaus & Maklan, 2013; Lemon & Verhoef, 2016). In the context of AI tool-driven e-commerce, these dimensions are further extended to include social interaction, as AI tools increasingly simulate human communication and relational engagement. Empirically, modeling CUE as a higher-order construct allows for a more comprehensive and parsimonious representation of CUE, capturing the integrated effect of all its subdimensions, such as customer satisfaction and loyalty.

2.2.1. Sensory Experience

Sensory experience (SSE) refers to the stimulation of customers' senses - such as vision, hearing, touch, and even multisensory integration - when they interact with a brand, product, or digital interface (Foroudi et al., 2025). Krishna (2012)'s integrative review on sensory marketing defines it as "marketing that engages the customers' senses and affects their perception, judgment, and behavior," highlighting those sensory cues (e.g., visuals, textures, sounds) can shape how customers perceive quality and meaning. In digital settings, sensory experience is mediated largely through visual and auditory channels, where interface design, imagery, audio feedback, animations, and microinteractions play a key role in conveying richness and realism (Hultén et al., 2009). A well-designed sensory interface can enhance immersion, aesthetic pleasure, and trust,

thereby elevating the overall customer experience.
In e-commerce, AI tools contribute significantly to enhancing SSE by customizing how sensory cues are delivered to customers. For instance, Grewal et al. (2023) show that in retail contexts, AI and smart in-store technologies enhance CUE by adapting presentation elements and optimizing customer interactions across touchpoints. By leveraging AI-driven algorithms, platforms can dynamically adjust visual layouts, image prominence, and interactive effects to match individual preferences, creating a more appealing sensory interface (Motoki et al., 2025). Further, research on human-AI sensory interaction suggests that AI systems can modulate sensory feedback to increase perceived authenticity and immersion (Foroudi et al., 2025). Emerging technologies such as AR/VR - often supported by AI - allow users to virtually "experience" products in rich sensory detail, helping bridge the gap between physical and online shopping contexts (Omeish, Al Khasawneh, et al., 2024). Through such mechanisms, AI acts not just as a backend engine of logic but as a mediator of sensory richness in customer interactions, reinforcing perceptions of personalization, engagement, and immersion in the digital commerce environment (Omeish, Sharabati, et al., 2024).

2.2.2. Emotional Experience

Emotional experience (EME) is about how customers feel - like happiness, anger, trust, or understanding - when they connect with a brand, product, or system (Satpute et al., 2015). These feelings are important for how customers judge and remember their experiences. For instance, Caruelle et al. (2024) talks about emotional reactions in CUE, showing that changes in good and bad emotions can greatly affect the overall customer experience. Emotions can be internal signals that change how people see service quality, affect satisfaction, and help build long-term loyalty (Marc Gobe, 2001). Besides that, EME depends not just on results (success or failure) but also on the tone, responsiveness, and perceived kindness of the interaction.

In e-commerce, AI tools affect how people feel by changing how "caring," "empathy," or "humanness" are shown through technology. For example, Chen et al. (2022) in the impact of emotional expression by AI suggests that emotional cues like text, emoticons, and images used by chatbots can make them seem more human and increase social interaction, which helps improve emotional engagement. Also, Chau et al. (2025) point out that emotional and functional satisfaction from AI interactions can make the overall experience in e-commerce better for customers. By adding emotional design elements like empathetic responses, messages that understand feelings, or mood changes, AI tool systems can create more positive feelings during interactions (Hao & Li, 2025). So, AI tools do more than just do tasks; they can build emotional connections, reduce customer stress, and increase trust, which helps make the emotional side of CUE stronger.

2.2.3. Social Experience

The social experience (SOE) among customer interactions refers to the sense of connection, belonging, and interaction that customers develop through their interactions with fellow customers, multiple communities, and the brand itself (Bandura, 1986). The experience extends beyond direct communication by including the reading of reviews, user reviews, and shared stories that work together to influence perceptions of credibility and authenticity. Lemon & Verhoef (2016) state that the CUE not only extends to individual interactions but also over into social arenas, where peer influence, brand communities, and social interactions work together to reinforce loyalty and attachment. In the digital commerce environment, sites reinforce SOE by including the features of community forums, customer reviews, and interactive online livestream shopping, collectively working to augment perceived credibility as well as foster relational connections (Verhoef et al., 2009).

AI technologies greatly elevate SOE by customizing the way customers engage in community-focused interactions (Omeish, Al Khasawneh, et al., 2024). For instance, the AI-based sentiment analysis will filter out and highlight actual reviews, while the recommendation technologies will make use of social confirmation by showing suggestions like "people like you also bought" (Grewal et al., 2023).

Chatbots and conversational AI also increasingly function as mediators of social communication by emulating one-on-one communication and removing obstacles to customer service. Research evidence suggests that the presence of the AI-based type of social commerce model enhances customers' sense of belonging and communal creativity within online communities, thereby deepening brand commitment and support (Mikalef & Gupta, 2021). By allowing scalable but personalized interactions, AI functions as an aggregator and an intermediary of social communication, thereby extending the overall customer experience environment.

2.3. Hypothesis Development

2.3.1. Customer Satisfaction

Customer satisfaction (CSA) is a multidimensional term that includes both a general assessment of the service (overall satisfaction) and a cognitive comparison of expected and actual performance (expectations fulfilled) (Bae, 2012). In other words, CSA is the consequence of confirming their expectations, and it is significantly related to the CUE. Customers who are influenced by utilitarian or functional objectives anticipate making a well-informed decision that aligns with their practical aims. In contrast, customers who are motivated by hedonic or experiential objectives seek to elicit positive emotions (i.e., enjoyment and exhilaration) or to evade adverse emotions stemming from the process of purchasing or engaging in consumption activities (Yuksel, 2008). Furthermore, CSA represents the transition stage, which includes customer loyalty and customer experience (Bae, 2012).

The deployment of AI tool-based assistance provides 24/7 support, quick responses to frequently asked questions, and more efficient and optimized allocation of complex issues to human staff (Ali et al., 2021). Predictive assistance, driven by data analytics, is capable of discerning potential complications prior to their escalation into significant problems, thereby enabling proactive customer support (Kushwah, 2025). These improvements will enhance the customer buying experience, making AI tools more user-friendly. Additionally, empirical studies converge on the positive impact of AI tools on CSA. Gnewuch et al. (2020) report that the information quality and responsiveness of AI tools directly predict CSA and continuance intention. Identically, Madanchian et al. (2023) illustrate the importance of personalization and efficiency in enhancing satisfaction within sustainable e-commerce frameworks. However, Huang & Rust (2018) caution that excessive automation or inadequate recommendation precision may undermine perceived authenticity and satisfaction. Collectively, AI tools elevate satisfaction by enhancing service quality, perceived utility, and personalization; however, these advantages are contingent upon transparency, equity, and ethical utilization of data.

H1. AI tools have a substantial impact on customer satisfaction in e-commerce.

Based on ECM, this investigation specifically examines the influence of e-commerce experiences on customer satisfaction and loyalty in the context of advancements in information technology and the development of AI technologies that aid users (Fu et al., 2018). The main elements of the e-commerce experience were interrelated with the triadic construct of e-commerce customer satisfaction, loyalty, and experience, as posited in the hypothesis. Moreover, the study establishes that customer satisfaction and experience are positively correlated (Liu et al., 2025). CSA serves as a mediating variable that promotes the core dimensions of CUE with AI tools in e-commerce, specifically regarding the interface quality, information accuracy, and the awareness of security risk mitigation and privacy considerations, all of which exert a favorable influence on both customer experience and satisfaction. These findings bear substantial implications for operators of e-commerce platforms, underscoring the necessity for enhancements in the relationship both satisfaction and overall experience.

H2. Customer satisfaction has a substantial impact on customer experience in e-commerce.

2.3.2. Customer Loyalty

Customer loyalty (CLO) constitutes one of the most pivotal metrics for customers and is a concept that has been extensively examined within the e-commerce research domain (Oliver, 1999). Trust fosters loyalty, which in turn leads to repeat purchases. Elevated levels of trust reflect a favorable customer perception of e-commerce (Ratner et al., 2025). Empirical evidence suggests that CLO has a significantly positive impact on customer satisfaction and experience. In addition to research assessing the mediating role of loyalty in e-commerce, there exists evidence suggesting that CLO partially mediates the relationship between the characteristics of AI tools and customer experience in the e-commerce sector (Wu & Mvondo, 2025).

AI tools are integral to the maintenance of CLO, which is characterized as the enduring, favorable inclination and repetitive purchasing tendencies that arise from satisfaction and allegiance (Lemon & Verhoef, 2016). According to Hao & Li (2025), AI tools enhance loyalty by fostering emotional connections and engagement through the provision of personalized and efficient services. Gnewuch et al. (2020) assert that the quality of service delivered by AI tools bolsters trust, which is a predictive factor for CUE. Furthermore, Ahmed & Aziz (2025) highlight that AI tools that promote empathy and adept problem-solving cultivate both affective and behavioral loyalty. A broader examination conducted by Lee & Breckon (2025) positions AI as a pivotal mechanism for the establishment of long-term relationships, thereby facilitating ongoing customer engagement. The research published by Adeola et al. (2024) in Springer underscores that interactions mediated by AI can forge relational bonds, particularly when customers recognize authenticity and transparency. In general, AI tools function as facilitators of loyalty within e-commerce ecosystems, contingent upon their design that prioritizes ethical personalization, transparency, and reliable engagement.

H3. AI tools have a substantial impact on customer loyalty in e-commerce.

Within AI-driven e-commerce environments, CLO constitutes a critical determinant of the customer experience continuum and exerts a reinforcing influence on subsequent experiential evaluations (Kandampully et al., 2017) as loyal customers engage more frequently and meaningfully with AI-enabled service interfaces, thereby co-create enhanced experiential value. CLO also demonstrates greater tolerance toward service imperfections, interpreting them through the lens of prior positive experiences, which further amplifies affective satisfaction (Ratner et al., 2025). CLO is a feedback mechanism that sustains a virtuous cycle of satisfaction and customer experience.

H4. Customer loyalty has a substantial impact on customer experience in e-commerce.

2.3.3. Customer Experience

Customer experience (CUE) represents the holistic journey of customers, from brand discovery to post-purchase interactions across many touchpoints (Meyer & Schwager, 2007). In essence, the CUE derives from the individual customer's subjective evaluations concerning all direct and indirect interactions (Shaw & Ivens, 2002). An experience within the e-commerce domain serves as a catalyst for CLO. Besides, poor e-commerce experiences can precipitate customer alienation and attrition (Bakkouri et al., 2022). Moreover, when customers participate in online activities and attain a flow state, they become completely absorbed and focused and derive pleasure from the experience. Thus, increased satisfaction and loyalty might result in a stronger emotional connection to the brand or platform (Lemon & Verhoef, 2016).

AI tools integration in e-commerce has reshaped how customers interact with online platforms (Shahsavar & Choudhury, 2023). This encompasses the customer's perceptions regarding the usability, efficacy, efficiency, and emotional satisfaction derived from AI technologies (Chau et al., 2025). In AI, the CUE includes the customer's subjective perspectives, preferences, and emotional reactions, as well as the system's functional features, such as accuracy and responsiveness (Lemon & Verhoef, 2016). AI tools such as chatbots, recommendation systems, and virtual assistants to provide faster responses, personalized services, and more efficient experiences. When customers perceive that AI tools enhance convenience and service quality, customers tend to experience greater satisfaction and engagement during their shopping journey (Hao & Li, 2025). Furthermore, interactive and intelligent AI services can generate emotional enjoyment, making it more immersive and memorable for customers (Foroudi et al., 2025). Importantly, this embedding means that CUE must be conceptualized as an experiential process that is constantly shaped by the mutual exchanges between intelligent systems and human users.

H5. AI tools have a substantial impact on customer experience in e-commerce.

The conceptual research model was developed from the above hypotheses, as illustrated in Figure 3.

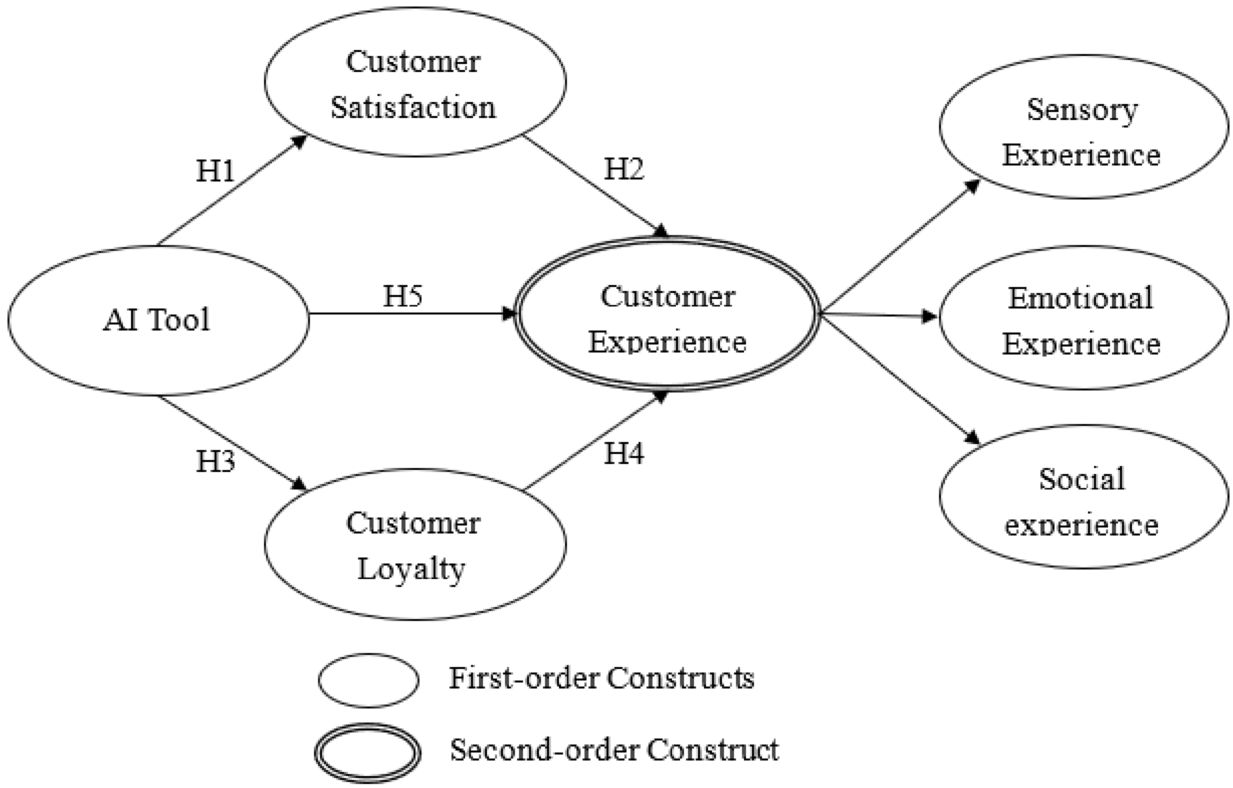

Figure 3. Conceptual research model

Source: Authors

3. Research Methodology

3.1. Research Design

Based on the comprehensive dataset collected from a structured survey, this research employs a quantitative, cross-sectional design to analyze how AI tool integration influences customer experience in e-commerce (Lim, 2024). The quantitative measure method and cross-sectional design were chosen for their efficiency and ability to reveal relationships at a single point in time (Lim, 2024). Thus, this design provides a systematic approach to gathering and statistically analyzing quantitative data, enabling the understanding of the impact of AI tools (AIT) on customer satisfaction (CSA), loyalty (CLO), and customer experience (CUE) in e-commerce.

A structured, self-administered online questionnaire was utilized to gather data from customers with and without prior experience using AIT-enabled e-commerce systems (Nguyen et al., 2025a).

Measurement items were drawn from previous validated studies on technology acceptance and customer experience (Lemon & Verhoef, 2016; Nguyen, Duc, et al., 2023) and were measured using a 7-point Likert scale, ensuring the consistency and comparability of the responses (Altuna & Arslan, 2016). Moreover, the online survey not only makes the study more widely accessible geographically but also more cost-effective and less prone to interviewer bias, which in turn strengthens the reliability and external validity of the study (Kumar, 2019). The ultimate objective of this research design is to generate actionable insights regarding the impact of AIT integration on CUE and to facilitate hypothesis testing via Partial Least Squares Structural Equation Modeling (PLS-SEM).

3.2. Target Population, Sample, and Data Collection Procedures

The target population of this study includes adult customers aged 18 and above in Ho Chi Minh City who have or have not interacted with e-commerce platforms that use AIT, such as chatbots, personalized recommendation systems, visual search, automated customer support, or virtual assistants, within the past twelve months. These individuals serve as the primary demographic, directly or indirectly engaging with AI-enhanced tools that significantly impact the customer experience within e-commerce. To ensure a diverse and representative sampling of customer segments, the study utilizes a non-probability quota sampling methodology, which is a rigorously established technique in e-commerce investigations when probability-based sampling frameworks are lacking (Taherdoost, 2016). The quotas are established based on salient demographic variables, such as age, gender, and frequency of online shopping behaviors, thus accurately mirroring the structural composition of e-commerce users in an urban environment like Ho Chi Minh City (Quan et al., 2023).

The quantitative component of the study required a minimum sample size of 92 participants. The final sample size was 206 responders (n = 206), which is much higher than the needed minimum. This sample size is considered sufficient to capture meaningful variance across key constructs, including AIT interaction, customer satisfaction, loyalty, and overall customer experience. Furthermore, it fulfills the methodological prerequisites necessary for performing descriptive and multivariate analyses, particularly structural equation modeling (SEM), which involves the estimation of both first-order and second-order latent constructs (Tri-Quan Dang et al., 2025). The specified sample size guarantees sufficient statistical power for identifying medium effect sizes and confidence intervals, thereby augmenting the precision and reliability of parameter estimations.

Quantitative data will be collected primarily through a structured online questionnaire administered via Google Forms, which includes validated measurement items and descriptions adapted from previous studies focused on technology acceptance, personalization, customer experience, loyalty, and customer satisfaction. The questionnaire is designed in a bilingual format (Vietnamese and English) to maximize accessibility and comprehension, as the majority of AI-tool users in Vietnamese e-commerce contexts are native speakers (Lim, 2024). The average duration for respondents to complete the survey was estimated to be between seven and ten minutes. The survey encompasses two sections: one addressing demographic profiles and the other concerning factors that influence the interaction between AIT and CUE within the e-commerce sector. All respondents were informed that their data would be utilized exclusively for academic analysis and kept private (T. Q. Dang et al., 2025; Duc et al., 2024; Le et al., 2025; Nguyen et al., 2025b; L.-G. N. Phan et al., 2025).

3.3. Measurement Scales

The measurement scales utilized in this investigation were meticulously designed based on established scales that were adapted from previously conducted empirical studies within the fields of AI, CUE, CSA, and CLO in the context of e-commerce. Each measurement item was formulated employing a 7-point Likert scale, which spans from 1 = strongly disagree to 7 = strongly agree, thereby effectively capturing the respondents' levels of agreement and the intensity of their attitudes towards each statement (T. Q. Dang, Duc, et al., 2025; T.-Q. Dang, Nguyen, Tran, et al., 2025; Le, Nguyen, et al., 2025; A.-H. D. Nguyen et al., 2024; L.-T. Nguyen et al., 2022). The selection of a 7-point scale over 5-point alternatives was motivated by its superior sensitivity, variance, and reliability in discerning nuanced differences in the participants' perceptions and behavioral inclinations (Altuna & Arslan, 2016; Finstad, 2010).

In relation to sample adequacy, a power analysis was conducted using the G∗Power software (version 3.1.9.7) to find out how many minimum samples needed for testing in statistics (Duc et al., 2025; L.-T. Nguyen, Duc, et al., 2023; L.-T. Nguyen, Nguyen, et al., 2023; L.-T. Nguyen, Phan, et al., 2025; N. T. T. Nguyen et al., 2024). The value for the G*Power software was calculated in relation to a family of statistical F tests (Linear multiple regression: Fixed model, deviation of R^2 from zero). The input variables in relation to power analysis were considered as follows: Test power of 0.80 ($1-\beta = 0.80$), alpha value of 0.05 ($\alpha = 0.05$), and an effect size F^2 of 0.15 ($f^2 = 0.15$) with 5 predictive variables (T.-Q. Dang, Nguyen, & Thi, 2025; Dao et al., 2023; B.-H. T. Nguyen et al., 2024; B.-T. H. Nguyen, Le, et al., 2023; L.-T. Nguyen et al., 2024). The power analysis revealed that a minimum of 92 samples was required. In order to improve its strength and possibilities of generalization, this study carefully gathered samples to a total of 206 valid responses (n = 206), which is more than the minimum recommended in G*Power and a minimum of 10 samples in an SEM in scope (Monecke & Leisch, 2012).

3.4. Data Analysis

The principal analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via the SmartPLS software platform (Binh et al., 2024; T. – T. C. Phan et al., 2025; Thi Viet & Nguyen, 2025). This methodological approach was selected due to its appropriateness for the research objectives and the specific characteristics of the data in this study (Edeh et al., 2023). Notably, PLS-SEM is particularly advantageous for exploratory and predictive research endeavors, wherein the emphasis is placed on identifying the principal determinants of target constructs, rather than on testing a well-established theoretical framework (Hair & Alamer, 2022). Within this study, the structural model comprises multiple latent constructs, each associated with several reflective indicators, thereby rendering model complexity an important consideration. Moreover, PLS-SEM does not necessitate adherence to the assumption of multivariate normality, which renders it suitable in contexts where data may contravene the assumptions underpinning covariance-based SEM. Concerning sample size, the investigation included a total of 206 valid responses, surpassing the traditionally accepted "5-times rule" and fulfilling more stringent minimum sample size criteria for PLS-SEM, thereby ensuring adequate statistical power for reliable estimations (Hair & Alamer, 2022). Consequently, considering the complexity of the proposed model, data non-normality, and predictive focus, PLS-SEM was chosen as the most appropriate analytical technique. The initial phase of the primary analysis comprised an evaluation of the reliability and validity of the constructs through SmartPLS (Edeh et al., 2023). This process encompassed the examination of individual item reliability via factor loadings, internal consistency reliability through Cronbach's Alpha (CA) and Composite Reliability (CR), as well as the confirmation of convergent validity through Average Variance Extracted (AVE) (Nguyen, Duc, et al., 2023). Discriminant validity was verified using the Fornell-Larcker criterion and HTMT, followed by SEM analysis assessing predictor independence through the Variance Inflation Factor (VIF) (Akinwande et al., 2015). Following the validation of the measurement model and the confirmation of multicollinearity, the subsequent step involved the testing of the structural model to investigate the relationships among constructs. This phase included an analysis of significance levels and path coefficients (β values) to elucidate the interconnections between constructs (Chau et al., 2025). Furthermore, the coefficient of determination (R^2) was employed to evaluate the explanatory power of the model. This thorough analytical methodology fortifies the study's validity and reliability, providing substantial empirical evidence to underpin the evaluation of the hypotheses (Nguyen et al., 2025a).

4. Results and Discussion

4.1. Demographics

To elucidate the demographic composition of the research sample, an examination of respondents' demographic characteristics was conducted based on data collected through an online survey form, resulting in 206 valid responses after data cleaning (S. K. Ahmed, 2024). The survey results showed that women made up the majority of respondents (59.71%) across all age groups. The younger age groups of 18-22 (53 females) and 23-30 (56 females) had the most women. The survey results showed that women made up the majority of respondents (59.70%) across all age groups. The younger age groups of 18-22 (53 females) and 23-30 (56 females) had the most women. Conversely, male respondents constituted 40.29% of the overall sample, with a notable concentration within the 23-30 age group (32 males), followed by the 31-35 (24 males) and 18-22 (23 males) cohorts. These results imply that young adults aged 18 to 30, particularly females, represented the most active and engaged demographic within the e-commerce landscape. The substantial presence of this demographic underscores a pronounced level of digital literacy and receptiveness to technological advancements, alongside frequent engagement with AI-augmented shopping functionalities such as personalized recommendations and chatbots (Bakkouri et al., 2022).

In addition, the survey results indicated that a majority of participants (52.43%) reported engaging in online purchasing activities 3-6 times per month, while 22.33% indicated 0-2 purchases, 21.84% reported 6-10 purchases, and a mere 3.39% exceeded 10 purchases within a week. This pattern reveals a tendency towards consistent, albeit moderately infrequent, online shopping behavior, indicative of stable engagement rather than impulsive purchasing tendencies. In selecting an e-commerce platform, respondents prioritized traditional determinants such as brand reputation (77.67%), product diversity (73.79%), and delivery efficiency (71.36%) as the most significant factors influencing their choices. Among the platforms assessed, Shopee received the highest rating for its effective utilization of AI to enhance the CUE (79.13%), followed by TikTok (67.48%) and Lazada (33.01%), whereas other platforms collectively represented a mere 0.48%.

The survey results further demonstrated that a majority of respondents (54.85%) had employed AIT-such as visual search, chatbots, or virtual assistants-during their online shopping experiences. The frequency of engagement with AI features was notably high, with 45.15% of users reporting usage "sometimes" and an additional 36.89% employing them "usually" or "always," in contrast to only 13.11% who utilized them "rarely" and 4.85% who "never" engaged with them. Most respondents exhibited a favorable disposition towards AI-generated recommendations, with 50.49% expressing an increased likelihood of making purchases and 24.27% indicating they would certainly make additional purchases, while 24.27% reported a decreased likelihood of purchasing, and merely 1% noted no influence. These results show that AIT greatly increases the likelihood of making a purchase, which supports the idea that AI has a positive effect on the CUE. Aligning with the ECM and the UTAUT frameworks, the results suggest that when AI fulfills user expectations and delivers concrete performance advantages, such as personalization and user-friendliness engenders heightened user satisfaction and technology acceptance (Momani, 2020). Consequently, the implementation of a transparent, user-centered AI design is imperative for sustaining user engagement and enhancing CUEs within the e-commerce realm.

Table 1. Demographic profile results

Demographic Profile (n=206)

Items		Frequency	Percent
Gender	Female	123	59.71%
	Male	83	40.29%
Age	18 - 22 Years Old	76	36.89%
	23 - 30 Years Old	88	42.72%
	31 - 35 Years Old	37	17.96%
	36 - 40 Years Old	5	2.43%
	41 - 50 years old	0	0.00%
	Over 50 years old	0	0.00%
How many times on average do you shop online through e-commerce per week?	0 - 2 times	46	22.33%
	3 - 6 times	108	52.44%
	6 - 10 times	45	21.84%
	Above 10 times	7	3.39%
What is the main factor influencing your choice of an e-commerce platform? (chose many answers)	Price/discounts	136	66.01%
	Product variety	152	73.79%
	Brand reputation	160	77.67%
	Delivery efficiency	147	71.36%
	Customer service	106	51.46%
	AI tools	43	20.87%
Which e-commerce platform currently applies AI most effectively to enhance the shopping experience? (chose many answers)	Shoppe	163	79.13%
	Lazada	68	33.01%
	TikTok	139	67.48%
	Others	1	0.48%
Have you ever used AI tools (e.g, chatbots, virtual assistants, voice assistants, etc.) for e-commerce?	Yes	113	54.85%
	No	11	5.34%
	Maybe	82	39.81%
How often do you use AI tools (e.g, product	Always	19	9.22%

Demographic Profile (n=206)

Items		Frequency	Percent
recommendations, chatbots, AR try-on) on e-commerce?	Usually	57	27.67%
	Sometimes	93	45.15%
	Rarely	27	13.11%
	Never	10	4.85%
When AI suggests products that suit you, are you more likely to make a purchase compared to when there are no suggestions?	Definitely buy more	50	24.27%
	More likely to buy	104	50.49%
	Even less likely to buy	50	24.27%
	No difference	2	0.97%

Source: Authors

4.2. Common Method Biases

Due to the data gathered via a self-reported questionnaire, there are concerns regarding the validity and accuracy of responses provided by participants, as well as potential effects that may result from common method bias (CMB) between the independent and dependent variables (Kock et al., 2021). CMB may result if measurement errors occur due to the application of a single data collection or measurement technique, leading to overstated or underrated correlations between constructs (Kock et al., 2021). For purposes of this study, participants were informed that no clear rights or wrongs existed, with responses being kept confidential as well as anonymous so as to avoid probable response bias, as well as minimize socially desirable answers.

4.3. Measurement Model Assessment

4.3.1. Reliability and convergent validity

The measurement model was evaluated with a rigorous evaluation to ascertain that all constructs within the research framework satisfied the requisite criteria for reliability, convergent validity, and discriminant validity prior to advancing to the structural model analysis. In accordance with the methodologies proposed by Sarstedt et al. (2017), the assessment of construct reliability and validity was systematically conducted during the measurement model analysis. The metrics of composite reliability (rho_A and rho_C), outer loadings, and CA were utilized as indicators of construct reliability; values exceeding 0.7 signify a statistically significant level of reliability (Lux et al., 2023). As delineated in Table 2, the CR (rho_A and rho_C), outer loadings, and CA (both first-order and second-order) exhibited values ranging from 0.784 to 0.974, thereby surpassing the established minimum threshold of 0.70 for both indices. The evaluation of individual factor loadings and the average variance extracted (AVE) served to ascertain convergent validity (Henseler et al., 2015). Typically, individual factor loadings ought to exceed 0.70, while AVE values should surpass 0.5 (Akinwande et al., 2015).

Furthermore, the composite reliability metrics (rho_A and rho_C) exceeded the threshold of 0.70, thereby indicating that the constructs are measured with a high degree of accuracy, thus affirming the model's internal consistency (Fornell & Larcker, 1981). The AVE for all constructs surpassed the recommended benchmark of 0.50, thereby signifying robust convergent validity. The second-order construct, CUE, exhibited exceptionally high loadings (ranging from 0.953 to 0.968) across its three first-order dimensions: EME, SOE, and SSE. The reliability indices for CUE, encompassing a CA of 0.960 and composite reliability (rho_A and rho_C) of 0.960 and 0.974, alongside a high AVE of 0.926, substantiate that it constitutes a reliable and well-articulated higher-order construct that synthesizes sensory, emotional, and social experiences. In the context of this study, all factor loadings were greater than 0.70, and the AVE values for all first-order and second-order constructs exceeded 0.50. Consequently, the findings corroborated the convergent validity for all first- and second-order constructs.

Table 2. Composite Reliability, Loading, Cronbach's Alpha, and Average Variance Extracted (AVE) for first-order and second-order constructs.

Construct	Items	Loadings	Cronbach's alpha	Composite reliability (rho_A)	Composite reliability (rho C)	Average variance extracted (AVE)
First-order constructs						
AIT	**AIT1**	0.839	0.869	0.870	0.911	0.720
	AIT2	0.891				
	AIT3	0.876				
	AIT4	0.784				
CLO	**CLO1**	0.833	0.866	0.867	0.909	0.714
	CLO2	0.850				
	CLO3	0.848				
	CLO4	0.849				
CSA	**CSA1**	0.858	0.874	0.875	0.914	0.726
	CSA2	0.854				
	CSA3	0.850				
	CSA4	0.845				
EME	**EME1**	0.833	0.857	0.857	0.903	0.700
	EME2	0.857				
	EME3	0.822				
	EME4	0.835				
SOE	**SOE1**	0.817	0.859	0.860	0.904	0.703
	SOE2	0.851				

Construct	Items	Loadings	Cronbach's alpha	Composite reliability (rho_A)	Composite reliability (rho C)	Average variance extracted (AVE)
	SOE3	0.832				
	SOE4	0.853				
SSE	SSE1	0.845	0.858	0.860	0.904	0.702
	SSE2	0.836				
	SSE3	0.812				
	SSE4	0.857				
Second-order construct						
CUE	EME	0.968	0.960	0.960	0.974	0.926
	SOE	0.967				
	SSE	0.953				

Notes: Cronbach's alpha, Loadings, and Composite reliability (rho_A and rho_C) are above 0.7. Average variance extracted (AVE) is above 0.5. *Source:* by authors.

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, CUE = Customer Experience, SSE = Sensory Experience, EME = Emotional Experience, SOE = Social Experience.

4.3.2. Discriminant validity

According to Gefen & Straub (2005), discriminant validity is demonstrated when each measurement item exhibits a weak correlation with alternative constructs, barring those to which it is theoretically linked. To further substantiate discriminant validity, the cross-loadings of all first-order constructs were meticulously examined. The loading of each indicator on its designated construct (bold values along the vertical) surpassed its loadings on any other construct, thereby confirming that the indicators maintain a stronger association with their corresponding latent variables (Tri-Quan Dang et al., 2025). In alignment with the criteria posited by (Hair et al., 2016), an item's loading on its intended construct must exceed its cross-loadings on other constructs by a margin of at least 0.20. As presented in Table 3, all measurement items complied with this criterion, with primary loadings ranging from 0.784 to 0.891, while cross-loadings on alternative constructs remained significantly lower. This pattern provides unequivocal evidence of discriminant validity at the first-order level, indicating that each construct is empirically distinct and captures a unique dimension of the measurement model.

Table 3. Indicator loadings and cross-loadings for first-order

	AIT	CLO	CSA	EME	SOE	SSE
AIT1	**0.839**	0.672	0.657	0.641	0.620	0.657
AIT2	**0.891**	0.738	0.697	0.659	0.678	0.688
AIT3	**0.876**	0.675	0.700	0.646	0.660	0.655
AIT4	**0.784**	0.661	0.677	0.718	0.718	0.700
CLO1	0.709	**0.833**	0.735	0.704	0.723	0.709
CLO2	0.694	**0.850**	0.716	0.760	0.754	0.746
CLO3	0.680	**0.848**	0.739	0.680	0.689	0.734
CLO4	0.657	**0.849**	0.734	0.740	0.773	0.750
CSA1	0.764	0.748	**0.858**	0.740	0.758	0.710
CSA2	0.697	0.698	**0.854**	0.715	0.684	0.704
CSA3	0.624	0.740	**0.850**	0.710	0.724	0.717
CSA4	0.653	0.762	**0.845**	0.743	0.713	0.715
EME1	0.660	0.734	0.710	**0.833**	0.779	0.732
EME1	0.660	0.734	0.710	**0.833**	0.779	0.732
EME2	0.682	0.721	0.739	**0.857**	0.777	0.765
EME2	0.682	0.721	0.739	**0.857**	0.777	0.765
EME3	0.638	0.707	0.685	**0.822**	0.778	0.706
EME3	0.638	0.707	0.685	**0.822**	0.778	0.706
EME4	0.650	0.695	0.723	**0.835**	0.738	0.730
EME4	0.650	0.695	0.723	**0.835**	0.738	0.730
SOE1	0.660	0.709	0.676	0.742	**0.817**	0.681
SOE1	0.660	0.709	0.676	0.742	**0.817**	0.681
SOE2	0.671	0.741	0.723	0.801	**0.851**	0.766
SOE2	0.671	0.741	0.723	0.801	**0.851**	0.766
SOE3	0.676	0.755	0.741	0.771	**0.832**	0.767
SOE3	0.676	0.755	0.741	0.771	**0.832**	0.767
SOE4	0.641	0.712	0.694	0.761	**0.853**	0.711
SOE4	0.641	0.712	0.694	0.761	**0.853**	0.711
SSE1	0.757	0.753	0.724	0.770	0.742	**0.845**

	AIT	CLO	CSA	EME	SOE	SSE
SSE1	0.757	0.753	0.724	0.770	0.742	**0.845**
SSE2	0.666	0.742	0.743	0.712	0.718	**0.836**
SSE2	0.666	0.742	0.743	0.712	0.718	**0.836**
SSE3	0.620	0.678	0.629	0.698	0.698	**0.812**
SSE3	0.620	0.678	0.629	0.698	0.698	**0.812**
SSE4	0.626	0.739	0.701	0.755	0.767	**0.857**
SSE4	0.626	0.739	0.701	0.755	0.767	**0.857**

Note: The cross-loading values (in bold along the vertical) surpass the inter-construct correlations, supporting discriminant validity. *Source:* by authors.

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, SSE = Sensory Experience, EME = Emotional Experience, SOE = Social Experience.

To evaluate the presence of multicollinearity and the robustness of the indicators embedded within the measurement model, the VIF values alongside the outer loadings were scrutinized for all first-order constructs. All observed VIF values are significantly lower than the critical benchmark of 5.0, as stipulated by Hair et al. (2014), thereby affirming the nonexistence of multicollinearity among the indicators. Specifically, the values of 1.628 and 3.291, which are considerably beneath the established threshold, substantiate that multicollinearity did not pose a problem in this investigation. This finding guarantees that the items incorporated within each construct are sufficiently distinct and do not introduce redundancy within the measurement model.

Table 4. VIF outer loading for first-order

Construct	VIF
AIT1	2.124
AIT2	2.769
AIT3	2.607
AIT4	1.628
CLO1	1.982
CLO2	2.109
CLO3	2.173
CLO4	2.182
CSA1	2.175

Construct	VIF
CSA2	2.222
CSA3	2.230
CSA4	2.150
EME1	2.716
EME1	1.938
EME2	2.184
EME2	2.930
EME3	2.734
EME3	1.879
EME4	2.034
EME4	2.456
SOE1	1.855
SOE1	2.373
SOE2	2.089
SOE2	3.291
SOE3	1.915
SOE3	2.819
SOE4	2.148
SOE4	2.711
SSE1	2.027
SSE1	2.648
SSE2	2.497
SSE2	2.022
SSE3	1.834
SSE3	2.205
SSE4	2.902
SSE4	2.155

Note: Variance Inflation Factor (VIF) values are smaller than 3.30. *Source:* by authors.

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, SSE = Sensory Experience, EME = Emotional Experience, SOE = Social Experience.

4.4. Structural Model Assessment

To enhance the verification of the discriminant validity outcomes, an analysis of the HTMT ratio was performed among the second-order constructs (Tri-Quan Dang et al., 2025). As delineated by Henseler et al., (2015), values that fall below 0.85 are indicative of robust discriminant validity, whereas values ranging from 0.85 to 0.90 are deemed acceptable for conceptually interconnected constructs. In this instance, all HTMT values surpass 0.90 , with certain pairs even nearing or exceeding 1.00, notably between CSA and CLO = 0.994 and between CUE and CLO = 0.985.

Table 5. Hetero-Trait-Mono-Trait (HTMT) assessment for second-order constructs

	Original sample (O)	**Sample mean (M)**	**2.50%**	**97.50%**
CSA ↔ AIT	0.922	0.923	0.863	0.973
CLO ↔ AIT	0.934	0.934	0.861	0.994
CSA ↔ CLO	0.994	0.994	0.945	1.042
CUE ↔ AIT	0.899	0.899	0.822	0.959
CUE ↔ CLO	0.985	0.985	0.947	1.019
CUE ↔ CSA	0.958	0.958	0.919	0.992

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, CUE = Customer Experience.

The bootstrapping technique, employing 5,000 subsamples, no sign alterations, and 99% bias-corrected confidence intervals, was implemented for the inferential statistical analysis (Tri-Quan Dang et al., 2025). The outcomes pertaining to the hypothesis (H) testing are depicted in Figure 4 and Table 6. All constructs, encompassing the relationship between AIT and CSA ($\beta = 0.806$, p_value < 0.005), CSA and CUE ($\beta = 0.328$, p_value < 0.005), the association of AIT with CLO ($\beta = 0.811$, p_value < 0.005), and CLO and CUE ($\beta = 0.474$, p_value < 0.005), exhibited statistically significant correlations with perceived value. Furthermore, the AIT was found to exert a significant influence on the CUE ($\beta = 0.173$, p_value < 0.005). Consequently, each of the hypotheses subjected to testing was validated and confirmed.

Table 6. Results of hypothesis testing

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics |O/STDEV|	P values	2.50 %	97.50 %	Remark
H1	AIT → CSA	0.806	0.807	0.028	28.659	0.000	0.748	0.858	Supported
H2	CSA → CUE	0.328	0.330	0.058	5.630	0.000	0.216	0.450	Supported
H3	AIT → CLO	0.811	0.812	0.032	25.329	0.000	0.743	0.869	Supported
H4	CLO → CUE	0.474	0.476	0.079	6.014	0.000	0.322	0.629	Supported
H5	AIT → CUE	0.173	0.169	0.079	2.195	0.028	0.011	0.317	Supported

Notes: P values are not greater than 0.05, T statistics (|O/STDEV|) are greater than 1.963, and confidence intervals (2.50% and 97.50%) are greater than 0, which hypothesis is supported. *Source:* by authors.

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, CUE = Customer Experience.

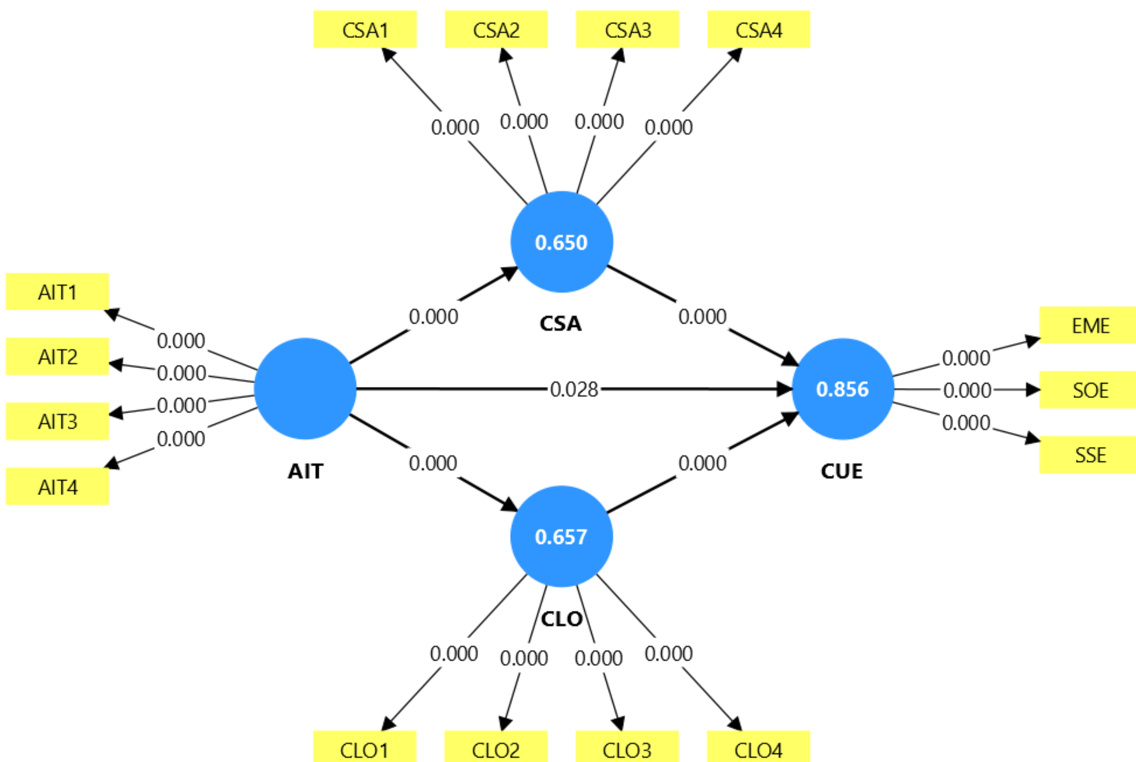

Figure 4. Results of hypothesis testing

Source: Authors

4.5. Effect Size and Predictive Relevance

The analysis of effect size (f^2) and predictive relevance (R^2) further validates the strength and practical significance of the model (Wang et al., 2024). The effect sizes for the impact of AIT on CLO (f^2 = 1.919) and CSA (f^2 = 1.854) are substantial, confirming that AIT is a major driver of these constructs. The effects of the mediators on the outcome are also meaningful; the impact of CLO on CUE (f^2 = 0.336) is medium-sized, while the effect of CSA on CUE (f^2 = 0.165) is small-to-medium. The very small effect size for the direct path from AIT to CUE (f^2 = 0.062) reinforces the conclusion that its direct effect is negligible compared to its indirect effects. Most importantly, the model demonstrates exceptional predictive power, as shown by the R-square values (Nguyen, Duc, et al., 2023). The model explains a high proportion of variance in CLO (R^2 = 0.657) and CSA (R^2 = 0.650). Most notably, it explains an impressive 85.6% of the variance in the overall CUE (R^2 = 0.856). This high explanatory power confirms that the integrated model, combining the direct effect of AIT with the critical mediating effects of satisfaction and loyalty, is highly effective at capturing the dynamics that shape CUE in e-commerce.

Table 7. Effect size R-square for second-order constructs

Construct	R-square	R-square adjusted
CLO	0.657	0.656
CSA	0.650	0.648
CUE	0.856	0.854

Source: by authors.

Abbreviations: CSA = Customer Satisfaction, CLO = Customer Loyalty, CUE = Customer Experience.

Table 8. Effect size f^2 for second-order constructs

Contruct	AIT	CLO	CSA	CUE
AIT		1.919	1.854	0.062
CLO				0.336
CSA				0.165
CUE				

Source: by authors.

Abbreviations: AIT = Artificial Intelligence Tools, CSA = Customer Satisfaction, CLO = Customer Loyalty, CUE = Customer Experience.

4.6. Discussion

The structural model analysis provides robust empirical support for all five proposed hypotheses, thereby confirming the central premise that the integration of AIT significantly enhances the e-commerce customer experience, primarily through the mediating mechanisms of CSA and CLO. The findings reveal a nuanced pattern in how AIT exerts its influence on customer behavior and perceptions.

Hypotheses H1 and H3 are strongly supported, demonstrating that AIT exerts a substantial direct effect on both CSA (β = 0.806, p_value = 0.000) and CLO (β = 0.811, p_value = 0.000). These represent the most pronounced path coefficients in the model, underscoring that AI-driven functionalities as personalized recommendations, responsive chatbots, and visual search systems-directly foster customer contentment and reinforce behavioral loyalty, including repeat purchasing and brand advocacy (Deng, 2022).

The results also confirm H2, indicating that CSA serves as a significant antecedent to the overall CUE (β = 0.328, p_value = 0.000). Customers who are satisfied with the performance and service quality of an e-commerce platform tend to evaluate their entire interaction journey more positively. Similarly, H4 is supported, showing that CLO exerts a particularly strong influence on the overall CUE (β = 0.474, p_value = 0.000). This highlights that loyal customer, who have developed positive emotional ties with the brand, are more inclined to perceive and interpret their interactions as superior.

Although H5 confirms a direct relationship between AIT and the overall CUE (β = 0.173, p_value = 0.028), this effect is noticeably weaker than the indirect effects transmitted through satisfaction and loyalty. This finding emphasizes that AI technologies alone do not guarantee an enhanced customer experience. Instead, their primary contribution lies in their capacity to cultivate satisfaction and loyalty, which subsequently elevates the perceived quality of the overall experience. Hence, AI's impact on customer experience operates predominantly through these mediating psychological and relational mechanisms.

The overall pattern of results delineates a clear causal pathway in which AI technologies act as the initial stimulus, whose efficiency and personalization capabilities enhance satisfaction and foster loyalty (Wu & Mvondo, 2025). These emotional and cognitive responses, in turn, lead customers to perceive a richer and more favorable experience. This integrated model effectively bridges the UTAUT, which focuses on pre-adoption perceptions of technological usefulness, and the ECM, which centers on post-adoption satisfaction and continued usage (Singh, 2020). Together, these frameworks elucidate how satisfaction and loyalty mediate the progression from technology adoption to superior experiential outcomes (H. Joshi, 2025).

Finally, the model demonstrates strong predictive power, with an R^2 value of 85.6% for CUE, indicating that the proposed framework explains the majority of variance in the outcome variable. For e-commerce practitioners, these results carry significant managerial implications: the strategic deployment of AI should transcend mere automation and operational efficiency (Chau et al., 2025). To truly elevate the customer experience, AI systems must be deliberately designed to enhance satisfaction and nurture long-term loyalty, as these are the proven pathways to sustained experiential excellence.

5. Implications, Conclusions, Limitations and Future Research Directions

5.1. Implications

5.1.1. Theoretical Contributions

This research makes significant theoretical contributions to the expanding body of knowledge regarding AIT adoption and CUE in e-commerce. First, it extends prior research by integrating the UTAUT with the ECM to establish a comprehensive theoretical framework that connects AI adoption to overall experiential outcomes (Fu et al., 2018; Hossain & Quaddus, 2011). This integrated model deepens theoretical understanding by elucidating not only the direct effects of AIT on CUE but also their indirect influence through the mediating processes of customer satisfaction and loyalty. Second, this study addresses a notable research gap in the existing literature, which has largely examined either the technological adoption of AI or its immediate effects on satisfaction and loyalty, while overlooking their combined impact on the holistic CUE. By bridging these perspectives, the present research offers a more integrated explanation of how AIT functionalities convert into sustained experiential value. Finally, reconceptualizing CUE as a second-order construct composed of sensory, emotional, and social dimensions advances theoretical discourse by introducing a multidimensional understanding of how consumers perceive and interpret AI-enabled e-commerce interactions (Lemon & Verhoef, 2016; Schmitt, 1999). As a whole, these contributions establish a coherent framework that explains how AI capabilities shape not only customers' behaviors but also their emotional responses and evaluative judgments, thereby offering a richer theoretical lens on technology-driven customer experience formation.

5.1.2. Managerial Implications

From a managerial perspective, the findings underscore a necessary transformation in the way e-commerce enterprises should reconceptualize customer relationship management in the era of AI (Nguyen et al., 2025a). Traditionally, managerial emphasis has revolved around strategies aimed at enhancing CSA and CLO as the ultimate objectives of marketing and service initiatives (Li et al., 2025). However, with the integration of AIT into management and customer interaction paradigms, the interrelationship among satisfaction, loyalty, and experience evolves into a mutually reinforcing dynamic rather than a sequential one. The integration of AIT empowers organizations to transcend reactive satisfaction and loyalty initiatives in favor of proactive experience management. Through real-time personalization, predictive analytics, and adaptive service frameworks, AIT allows managers to anticipate customer needs, deliver emotionally resonant interactions, and create consistent value throughout the digital journey (Liu et al., 2025). This approach not only strengthens satisfaction and loyalty but also amplifies the overall customer experience, thereby establishing a virtuous cycle.

Consequently, managers should embrace a strategic orientation towards AI that regards customer satisfaction, loyalty, and experience as interconnected dimensions of long-term value creation. By embedding AI within customer relationship management systems, firms can transition from transactional engagement to experiential engagement, where technology supports empathy, trust, and continuity in customer relationships (Reitsamer & Becker, 2024). This approach requires aligning AI investments with broader organizational objectives of relationship quality and customer-centric innovation, ensuring that AI becomes not only a tool of efficiency but also a catalyst for enduring experiential excellence.

5.2. Limitations and Future Research Directions

Despite its theoretical and managerial contributions, this study acknowledges several limitations that provide opportunities for future research. First, the research employed a cross-sectional quantitative design based on self-reported perceptions, which may introduce response bias or common method variance (Kock et al., 2021). Future studies could utilize longitudinal or mixed-method approaches to capture behavioral dynamics and causal relationships over time, offering a deeper understanding of how AI-driven satisfaction and loyalty evolve across repeated interactions.

Second, the sample primarily consisted of young Vietnamese e-commerce users, which may constrain the generalizability of the findings. Future research could expand to include diverse demographic profiles and cross-cultural samples to explore whether age, cultural background, or purchasing behavior moderates the relationship between AI adoption, satisfaction, and customer experience. Such comparative analyses could uncover nuanced differences in AI perception between developed and emerging markets.

Third, this study concentrated on major AIT in general without distinguishing their specific functional and experiential impacts (Akdemir & Bulut, 2024). Subsequent research could differentiate between various AI technologies, including generative AI, chatbots, recommendation systems, virtual assistants, augmented reality (AR), and voice-based commerce to evaluate how each contributes uniquely to customer satisfaction, loyalty, and experience formation.

Additionally, emerging ethical and social considerations surrounding AI, such as data transparency, algorithmic fairness, and perceived intrusiveness, serve as boundary conditions influencing how customers evaluate AI-driven interactions (Gao et al., 2025). Incorporating these variables as moderators would help construct a more comprehensive and context-sensitive model.

Finally, future research could extend this framework to other industries such as healthcare, education, hospitality, and tourism to examine the universality and adaptability of AI-enabled experiential mechanisms (Mariani & Borghi, 2021). By broadening the model across multiple service contexts and integrating behavioral, emotional, and ethical dimensions, future studies can enrich both academic theory and practical understanding of how AI continues to transform customer experience in the digital era.

5.3. Conclusions

This study finds that AIT significantly improves customer satisfaction, loyalty, and overall experience in e-commerce. The structural model indicated that AI influences CUE through CSA and CLO, achieving an R^2 of 0.856, which highlights the mediating role of these factors. When AIT meets customer expectations, they are useful, reliable, and emotionally engaging. They enhance satisfaction and loyalty, enriching the overall experience. This research positions AI not just as a technological facilitator but as a relational medium that collaborates with customers to create value. Utilizing the integrated UTAUT-ECM framework, it offers insights into both adoption and post-adoption behaviors in digital CUE, addressing a crucial theoretical gap. Ultimately, the study confirms that AIT's impact on CUE in e-commerce is complex and mainly indirect, heavily mediated by CSA and CLO. AIT acts as a catalyst, improving satisfaction through effective service and fostering loyalty via personalized engagement. These psychological outcomes are vital in enhancing the overall customer experience, illustrating the importance of ensuring AIT implementation leads to satisfied and loyal customers.

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Appendix

Appendix A

Table 9. Measurement items

Constructs	Description Items	References
AI Tools (AIT)	AIT1: "I feel AI tools enhance my experience in e-commerce." AIT2: "I am likely to buy unplanned goods or services supported by AI tools." AIT3: "Learning how to use shopping apps and websites powered by AI tools is easy for me." AIT4: "I find it useful when I get personalized recommendations from AI tools."	(Chau et al., 2025; Ratner et al., 2025)
Customer Satisfaction	CSA1: "I will use the AI tools of the e-commerce I have used again if I need to."	(Chau et al., 2025; Gao et al., 2025)

Constructs	Description Items	References
(CSA)	CSA2: "I am satisfied with the experience of using this AI-powered service system (e.g., product search, quality of information on products or services, product comparison)." CSA3: "I am pleased with my experience using AI tools in e-commerce." CSA4: "The AI tools in e-commerce that I am currently using meet my expectations."	
Customer Loyalty (CLO)	CLO1: "I intend to keep purchasing from e-commerce with AI tools." CLO2: "I consider myself loyal to AI-powered platforms." CLO3: "I recommend to family and friends the use of e-commerce platforms with AI tools." CLO4: "I will buy other products from e-commerce platforms in the future through AI recommendations."	(Mofokeng, 2023; Ratner et al., 2025)
Sensory Experience (SSE)	SSE1: "I find the colors used in AI-tool-based e-commerce interfaces very appealing." SSE2: "The design style of AI tools on e-commerce websites is appealing to me." SSE3: "I have positive sensory experiences with AI features in e-commerce." SSE4: "I believe AI-enabled sensory designs (visuals, colors, music) improve my e-commerce shopping experience."	(Foroudi et al., 2025; Omeish, Al Khasawneh, et al., 2024)
Emotional Experience (EME)	EME1: "Interacting with AI tools in e-commerce shopping excites me." EME2: "AI-driven e-commerce recommendations make	(Foroudi et al., 2025; Omeish, Al Khasawneh, et al.,

Constructs	Description Items	References
	me feel happy." EME3: "I have a positive overall attitude towards AI tools in e-commerce." EME4: "AI tools on e-commerce offer me enjoyable and efficient shopping experiences."	2024)
Social Experience (SOE)	SOE1: "I am more likely to purchase products promoted by AI-driven influencers in e-commerce." SOE2: "I tend to follow AI-driven influencers or product recommendations on e-commerce websites." SOE3: "I have positive social experiences with AI tools in e-commerce." SOE4: "I consistently find AI tools' promotional materials on e-commerce websites attractive."	(Foroudi et al., 2025; Omeish, Al Khasawneh, et al., 2024)