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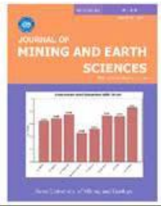

The impact of artificial intelligence technology on purchase decisions in B2C e-commerce: An electronic service quality perspective

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ABSTRACT

This study aims to examine customers' responses to AI-enabled services during the shopping process on B2C e-commerce platforms in Vietnam from an electronic service quality perspective. Drawing upon Customer Experience Theory (CET) and the Stimulus–Organism–Response (S-O-R) framework, the study investigates the effects of AI-enabled service experiences on online purchase decisions while examining the mediating role of perceived electronic service quality and the moderating role of customers' technology readiness. A quantitative research approach was employed, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings, based on a survey of 298 customers who had previously shopped and used AI-enabled services on B2C e-commerce platforms in Vietnam, indicate that the application of AI in service delivery can generate both positive and negative effects on purchase decisions through customers' perceptions of electronic service quality. In addition, technology readiness was identified as a significant moderating factor that strengthens the relationship between AI-enabled service experiences and perceived electronic service quality. Based on the empirical findings, the study contributes to reinforcing the theoretical logic of the S-O-R framework and extending the explanatory power of Customer Experience Theory in the context of AI-enabled e-commerce. The study also provides several managerial implications for e-commerce platforms and online retailers regarding the implementation and personalization of AI-enabled services to enhance electronic service quality and stimulate customer purchasing behavior.

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1. Introduction

In recent years, e-commerce in Vietnam has grown rapidly in both market size and growth rate. Vietnam is currently the third-largest e-commerce market in Southeast Asia, after Indonesia and Thailand, and recorded the highest e-commerce growth rate in the region in 2023 (Momentum Works, 2024). According to the Vietnam E-commerce Index Report for the 2020–2025 period published by the Vietnam E-commerce Association, the online retail market increased from USD 13.2 billion in 2020 to USD 32 billion in 2024, with an average annual growth rate of 15-27%, and is expected to reach approximately USD 39 billion by 2025 (Google; Temasek and Bain&Company, 2024). At the same time, the rapid growth in Internet users has continued to support the expansion of e-commerce. As of January 2025, Vietnam had around 79.8 million Internet users, accounting for 78.8% of the population; among them, 78% participated in online shopping and 61% had purchased products on e-commerce platforms (E-commerce and Digital Economy Agency, 2023; We Are Social & Meltwater, 2025). These figures show that online shopping has become a common consumer behavior and an important part of daily life in Vietnam. Currently, e-commerce platforms are the main online shopping channel, with the percentage of users who have purchased on Shopee reaching 81%, followed by Lazada (42%), TikTok Shop (34%), and Sendo (8%) (E-commerce and Digital Economy Agency, 2023).

The rapid growth of the market has also increased competition, especially as international e-commerce platforms enter Vietnam with advantages in pricing, logistics, and technology. In the context of shrinking profit margins, Vietnamese e-commerce platforms find it difficult to maintain competitive advantages based only on pricing strategies (Sapo Technology JSC, 2025). Therefore, electronic service experience and electronic service quality have become important and sustainable competitive advantages that help firms retain customers and maintain long-term growth. A key characteristic of B2C e-commerce is that the entire transaction and customer interaction process takes place in a digital environment, involving many touchpoints such as information search, consultation, ordering, payment, delivery, returns, and after-sales services. Consumers increasingly expect a shopping journey that is seamless, fast, and trustworthy; any problem in the service process may reduce perceived value, customer satisfaction, and revisit intention (Parasuraman et al., 2005; Zeithaml et al., 2002). In addition, risks related to fraud, counterfeit products, payment security, and personal data protection in Vietnam's e-commerce environment make digital trust a key factor closely associated with electronic service quality (Rita et al., 2019).

Rapid technological development, particularly in artificial intelligence (AI), is fundamentally changing service delivery in e-commerce. AI has been widely applied in functions such as customer service chatbots, personalized recommendation systems, image-based search, smart logistics, dynamic pricing, and automated after-sales services (Adam et al., 2021; Song et al., 2019). In Vietnam, major e-commerce platforms such as Shopee, Lazada, Tiki, and TikTok Shop have integrated AI into different stages of the shopping journey to improve operational efficiency and handle increasing transaction volumes. The application of AI not only optimizes service processes but also reshapes how consumers experience and interact with digital platforms, thereby raising expectations regarding electronic service quality.

Although AI has attracted significant attention from researchers, studies in the e-commerce field have mainly focused on algorithm performance and technical efficiency, while research from the consumer behavior perspective remains limited (Bawack et al., 2022). Recent studies suggest that AI-enabled services can improve customer experience, satisfaction, and the relationship between firms and customers (Asante & Jiang, 2023; Nguyen et al., 2021). However, previous findings are still inconsistent. Some studies argue that AI cannot completely replace human interaction in creating emotional value and trust and may even increase customers' perceived sacrifice during service use (Ameen et al., 2021; Mariani & Borghi, 2024; Prentice et al., 2020). These inconsistent findings indicate that the impact of AI-enabled services on customer behavior has not yet been fully clarified, especially from the perspective of electronic service quality.

In addition, most previous studies have treated AI as an independent technological factor or focused mainly on the technical quality of AI systems, while paying less attention to how AI-enabled service experiences influence customer behavioral responses through perceived electronic service quality (Noor et al., 2022). Studies on customer experience and electronic service quality have also mainly been developed in the context of traditional websites or online services and therefore may not fully reflect the intelligent interaction, personalization, and automation characteristics of AI-enabled services in modern e-commerce (Nguyen et al., 2021; Noor et al., 2022).

Furthermore, technology readiness (TR) reflects an individual's psychological tendency to accept and use new technologies through beliefs, attitudes, and emotions toward technology (Blut & Wang, 2020; Parasuraman, 2000). In the context of AI-enabled services, where technology systems become direct interaction agents, the role of TR goes beyond shaping initial perceptions and may moderate the relationships among service quality, perceived value, satisfaction, and customer behavior (Wang et al., 2017; Wirtz et al., 2018). This issue is particularly important in emerging markets such as Vietnam, where differences in digital experience and technology readiness may lead customers to evaluate AI-enabled services in very different ways (Nguyen et al., 2023; Parasuraman, 2000; Wang et al., 2017).

Based on these research gaps, this study aims to clarify the relationship between AI-enabled service experiences and online purchase decisions among consumers on B2C e-commerce platforms in Vietnam through the mediating role of perceived electronic service quality and the moderating role of technology readiness. The study approaches the issue from a service quality perspective and applies Customer Experience Theory (CET) and the Stimulus–Organism–Response (S-O-R) framework to explain the relationships among AI-enabled service experiences, customers' cognitive and emotional states, and behavioral responses. The research model was developed based on a literature review combined with in-depth interviews and was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) on survey data collected from consumers who had previously shopped on e-commerce platforms in Vietnam. Accordingly, the study contributes theoretically by extending the explanatory power of CET and the S-O-R framework in the context of AI-enabled e-commerce, while also providing managerial implications for e-commerce platforms and online businesses regarding the effective implementation of AI to enhance electronic service quality and encourage customer purchasing behavior.

2. Literature review and hypothesis development

2.1. Theoretical background

This study adopts a service quality perspective to examine online purchase decisions of consumers on B2C e-commerce platforms in the context of AI adoption. Service quality is defined as the gap between customers' expectations and their perceptions after experiencing a service (Parasuraman et al., 1985). Building on this foundation, the SERVQUAL model conceptualizes service quality as a multidimensional construct reflecting customers' subjective evaluations of service performance (Parasuraman et al., 1988). Empirical studies consistently demonstrate that perceived service quality serves as a critical antecedent to intermediate psychological states such as perceived value and satisfaction, which subsequently lead to behavioral outcomes including purchase intention and loyalty (Shi et al., 2014).

Within the e-commerce environment, AI has been increasingly integrated into service delivery through customer-facing applications such as intelligent chatbots, product recommendation systems, image-based search, interface personalization, and automated after-sales services (Saponaro et al., 2018). These AI applications are not merely technological tools but constitute integral elements of the digital service environment that consumers directly experience during their shopping journey. Accordingly, AI-enabled services can be viewed as a component of overall electronic service quality, with the potential to influence consumers' cognitive evaluations, emotional responses, and behavioral outcomes (Prentice et al., 2020).

To explain the mechanisms through which AI-enabled services affect online shopping behavior, this study integrates CET and the S-O-R framework. According to CET, customer value is formed through the overall consumption experience, encompassing both cognitive and affective responses arising from interactions with service elements (Urdea & Constantin, 2021). In online contexts, customer experiences may be either positive or negative; however, prior research has predominantly focused on positive experiences, while negative experiences, particularly those mediated by AI, remain underexplored (Nguyen et al., 2021; Rahman et al., 2023).

The S-O-R model, originally proposed by Mehrabian and Russell (1974), posits that environmental stimuli influence individuals' internal states, which in turn lead to behavioral responses (Mehrabian & Russell, 1974). Specifically, environmental stimuli (Stimulus) affect internal cognitive and emotional processes (Organism), ultimately resulting in behavioral responses (Response) (Ning Shen & Khalifa, 2012). These responses may manifest as approach behaviors such as exploration, engagement, and purchase decisions or avoidance behaviors, reflected in negative attitudes and refusal to purchase (Mehrabian & Russell, 1974). The S-O-R framework has been widely applied to explain consumer behavior across various domains, including tourism, retailing, and banking, as well as in e-commerce contexts to examine the effects of information quality, website quality, and online experiences on purchase and repurchase intentions (Herrando et al., 2019). Nevertheless, most existing studies emphasize approach responses, while avoidance responses have received limited empirical attention.

According to the logic of the S-O-R framework, the relationship between stimuli and internal states is not uniform but depends on individual characteristics that shape how stimuli are perceived and interpreted. In AI-enabled e-commerce settings, technology readiness represents a critical individual difference that governs this process. Grounded in CET and S-O-R, technology readiness does not directly generate experiences; rather, it moderates how AI-enabled service experiences are translated into perceptions of electronic service quality. When exposed to the same AI-enabled services, consumers with higher technology readiness are more likely to interpret AI interactions as signals of efficiency and convenience, whereas those with lower technology readiness may perceive them as indicators of risk or a lack of human touch, thereby diminishing perceived service quality.

In this study, CET and the S-O-R framework are employed to explain the mechanisms through which AI-enabled services influence online purchase behavior, while technology readiness is incorporated as a moderating variable grounded in the S-O-R logic of individual differences in processing environmental stimuli. This approach enables a more nuanced understanding of heterogeneity in perceived electronic service quality and purchase decisions among different consumer segments in the Vietnamese B2C e-commerce context.

2.2. Purchase decision

Purchase decision is a continuous process that involves consumers' careful and consistent evaluation of perceived alternatives prior to making a purchase, with the ultimate goal of satisfying their needs. It can be understood as an individual, situational, social, and context-dependent phenomenon (Engel et al., 1993). Consumers typically make purchase decisions based on factors such as place of purchase, brand, design, quantity, timing, price, and payment method. These decisions may be influenced by marketers through the provision of product or service information that informs consumers' evaluation processes.

Consumers are generally considered rational decision-makers who systematically utilize available information to arrive at purchase decisions (Ajzen, 1980). From a strategic marketing perspective, facilitating consumers' purchase decisions entails meeting the needs of target customers and enhancing perceived satisfaction (Porter, 1985). Purchase decisions may be modified or revised depending on situational factors and consumption contexts, which often stem from the quality characteristics of the service provider. In the present study, purchase decision is examined within the context of consumers' experiences with AI-enabled services on B2C e-commerce platforms.

2.3. The relationship between AI-enabled customer experience and purchase decision

Customer experience refers to consumers' cognitive, emotional, sensory, and behavioral responses across the consumption process (Lemon & Verhoef, 2016). Offline experiences are shaped by physical attributes, whereas online experiences are primarily driven by technology-related features such as interface design and usability (Keiningham et al., 2017; Lam, 2001). Customer experience thus represents a psychological state emerging from interactions with products or services (Tsaur et al., 2007).

In digital environments, consumers increasingly value experiential benefits, as online shopping relies mainly on visual and verbal stimuli rather than physical interaction (Lemon & Verhoef, 2016; Pine & Gilmore, 1999). Advances in AI have enabled firms to enhance customer experience through automated and intelligent interactions. Concepts such as "cyber atmospherics" highlight how virtual environments shape online experiences, while AI technologies facilitate personalized interactions based on customer data and prior experiences (Ameen et al., 2021; Pillarisetty & Mishra, 2022).

Managing customer experience has become central to marketing practice, as positive service experiences enhance perceived value and increase purchase likelihood (Amenuvor et al., 2019; Halim et al., 2023). Empirical evidence consistently demonstrates a positive relationship between customer experience and purchase behavior in service and retail contexts (Kumar et al., 2014).

In contemporary e-commerce settings, AI-enabled services are increasingly deployed to optimize customer experience across the shopping journey. Accordingly, customers' experiences with AI-enabled services are expected to positively influence their purchase decisions. Based on this reasoning, the following hypothesis is proposed:

H1: AI-enabled customer experience positively affects customers' purchase decisions.

2.4. Sacrificing customer perception toward AI-enabled services and purchase decision

Perceived sacrifice refers to the trade-offs consumers make to obtain a product or service, including both monetary and non-monetary costs such as time, effort, cognitive involvement, and psychological discomfort (Zeithaml, 1988). In online shopping contexts, perceived sacrifice may involve loss of control, privacy concerns, financial risk, and negative emotions experienced during the transaction process (Shin & Lin, 2016). Compared with monetary costs, non-monetary sacrifices are often more difficult for consumers to evaluate and manage (Ameen et al., 2021).

In AI-enabled service contexts, perceived sacrifice may be intensified by reduced human interaction, perceived social isolation, and increased reliance on personal data (Davenport et al., 2020). AI-driven services typically require users to adapt to predefined interaction structures, which may be perceived as demanding additional cognitive effort, particularly among less technologically experienced consumers (Ameen et al., 2021). The absence of human support can further increase time and effort costs, leading consumers to prefer a balance between automation and human involvement rather than full automation (Prentice et al., 2020).

These perceived sacrifices may generate discomfort and dissatisfaction, thereby discouraging purchase behavior in e-commerce settings. Accordingly, the following hypothesis is proposed:

H2: Perceived sacrifice toward AI-enabled services has a negative effect on customers' purchase decisions.

2.5. The mediating role of E-service quality

E-service quality (ESQ) reflects consumers' overall evaluations of services delivered through electronic interfaces, indicating the extent to which online platforms facilitate effective and efficient shopping, purchasing, and delivery processes (Carlson & O'Cass, 2012; Zeithaml et al., 2000). ESQ is formed through consumers' assessments across the entire online transaction process and has been consistently identified as a key determinant of behavioral intentions, including purchase decisions (Dhingra et al., 2020; Santos, 2003).

In AI-enabled e-commerce contexts, ESQ plays a particularly important role because many services are delivered via self-service systems. Positive experiences with AI-enabled services such as efficient interactions and personalized interfaces are expected to enhance perceived ESQ, thereby encouraging purchase behavior (Ameen et al., 2021). Conversely, perceived sacrifices associated with AI-enabled services, including reduced human interaction, loss of control, or privacy concerns, may undermine consumers' evaluations of ESQ and weaken their willingness to purchase (de Medeiros et al., 2016; Li & Shang, 2020).

Accordingly, ESQ is posited as a central mechanism through which both positive AI-enabled experiences and negative perceived sacrifices influence purchase decisions. Based on this logic, the following hypotheses are proposed:

H3: E-service quality mediates the relationship between AI-enabled customer experience and customers' purchase decisions.

H4: E-service quality mediates the relationship between perceived sacrifice toward AI-enabled services and customers' purchase decisions.

2.6. The moderating role of technology readiness

Technology readiness (TR) refers to an individual's psychological propensity to embrace and use new technologies to accomplish goals in work and daily life (Parasuraman, 2000). TR represents a constellation of relatively stable beliefs, attitudes, and emotions toward technology, thereby explaining inter-individual differences in technology adoption and responses to technological solutions (Blut & Wang, 2020).

According to the Technology Readiness Index (TRI) and its updated version TRI 2.0, TR comprises four dimensions: optimism (OP), innovativeness (INN), discomfort (DI), and insecurity (INS) (Parasuraman, 2000; Parasuraman & Colby, 2014). Optimism and innovativeness reflect positive enablers that facilitate technology acceptance, whereas discomfort and insecurity represent psychological barriers that hinder adoption (Blut & Wang, 2020). Most prior studies conceptualize TR as a multidimensional construct to capture the complexity of users' psychological orientations toward technology (Hassan et al., 2022), although some research has treated TR as a unidimensional index by aggregating its components (Choi & Yoo, 2021).

In online service and e-commerce contexts, empirical evidence suggests that TR is associated with perceptions of e-service quality and online behavior; however, findings remain limited and inconsistent (Liljander et al., 2006; Zeithaml et al., 2002). This inconsistency implies that TR does not necessarily exert a direct effect on behavior but may instead function as a contingent factor that shapes how consumers interpret and respond to technology-based services. Specifically, positive TR dimensions (optimism and innovativeness) tend to foster favorable attitudes toward technology-based services, whereas negative dimensions (discomfort and insecurity) weaken acceptance and increase resistance (Liljander et al., 2006; Zeithaml et al., 2002).

In AI-enabled e-commerce environments, where intelligent services are deeply embedded in interaction and personalization processes, differences in consumers' technology readiness may alter how service experiences are interpreted and how ESQ is evaluated. Consistent with the S-O-R framework, TR can be conceptualized as a personal characteristic that moderates the relationship between AI-enabled service experience (stimulus) and perceived e-service quality (organism). Accordingly, this study proposes the following moderating hypotheses:

H5a: The positive effect of AI-enabled customer experience on e-service quality is stronger when consumers' optimism and innovativeness toward technology are higher.

H5b: The negative effect of perceived sacrifice toward AI-enabled services on e-service quality is weakened when consumers' optimism and innovativeness toward technology are higher.

H6a: The negative effect of perceived sacrifice toward AI-enabled services on e-service quality is stronger when consumers' discomfort and insecurity toward technology are higher.

H6b: The positive effect of AI-enabled customer experience on e-service quality is weakened when consumers' discomfort and insecurity toward technology are higher.

Based on these hypotheses, the proposed research model is presented in Figure 1.

3. Research methodology and data analysis

3.1. Scale development and questionnaire design

A two-stage procedure was employed to develop the questionnaire and measurement scales. First, an extensive literature review was conducted in combination with expert interviews to identify, adapt, and refine existing measurement scales for the constructs included in the research model. This process ensured the content validity and initial reliability of the measurement instruments.

Second, a pilot survey involving 50 respondents was administered to review and refine the wording of the measurement items, thereby enhancing clarity, contextual appropriateness, and practical measurability.

After finalizing the questionnaire, the reliability of the measurement scales was assessed using Cronbach's alpha. The results indicated that all scales exceeded the recommended threshold of 0.7, confirming satisfactory reliability and construct validity for subsequent analyses (Hair et al., 2019).

Specifically, the measurement scales used in the questionnaire were as follows. AI-enabled customer experience was treated as an independent variable and measured using 10 items (EX1-EX10), adapted from Ameen et al. (2021). Perceived customer sacrifice toward AI-enabled services was also modeled as an independent variable and measured by 6 items (PS1-PS6), likewise adapted from Ameen et al. (2021). E-service quality was specified as a mediating variable and measured using 6 items (ESQ1-ESQ6), adapted from Halim et al. (2023). Purchase decision served as the dependent variable and was measured by 5 items (PD1-PD5), adapted from Shareef et al. (2008).

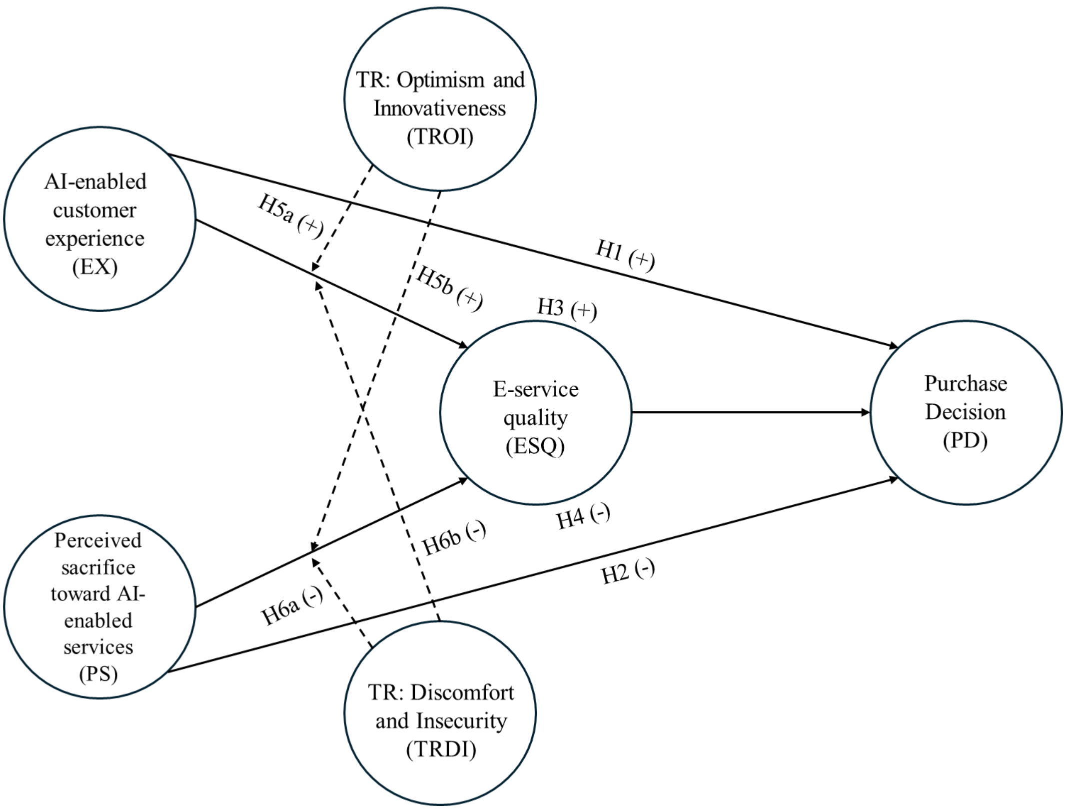

Figure 1. Research model.

(Source: Proposed by the authors).

Technology readiness was incorporated as a moderating variable. In line with the TRI 2.0 framework, optimism and innovativeness were measured using 4 items (TROI1-TROI4), while discomfort and insecurity were measured using 4 items (TRDI1-TRDI4), adapted from Parasuraman and Colby (2014).

3.2. Sampling and data collection method

The quantitative survey was conducted between October 2025 and December 2025 (Table 1). The target respondents were customers living and working in three major Vietnamese cities: Hanoi, Da Nang, and Ho Chi Minh City, who had prior shopping experience on major B2C e-commerce platforms such as Shopee, TikTok Shop, Lazada, and Tiki. Data were collected through an online survey administered via Microsoft Forms, employing a non-probability convenience sampling approach.

The measurement model comprised 35 observed variables. Following the guideline proposed by Hair et al. (1998), which recommends a minimum ratio of five observations per measurement item, the minimum required sample size was determined to be 175 observations (35 × 5) (Hair et al., 1998). The questionnaire consisted of 35 items measuring AI-enabled service experience, perceived sacrifice, e-service quality, technology readiness, and purchase decision. All measurement items were assessed using a five-point Likert scale ranging from "strongly disagree" to "strongly agree".

To ensure the required sample size, the authors distributed more than 500 survey questionnaires. A total of 356 responses were collected, of which 298 valid questionnaires were retained for further analysis after excluding responses that did not meet data quality requirements, such as incomplete or inconsistent answers. The research data were coded, processed, and analyzed using SmartPLS 4 software.

Table 1. Sample description.

Sample Description	Number of People	Percentage (%)
Gender		
Male	122	40.9
Female	176	59.1
Age		
18 to 23	123	41.3
24 to 30	98	32.9
31 to 40	55	18.5
Over 40	22	7.4
Occupation		
Student	108	36.2
Office worker	91	30.5
Specialized professions (Doctor, Teacher, Police, Engineer, Scientist)	67	22.5
Manual labor	24	8.1
Other	8	2.7
E-commerce platforms		
Shopee	296	99.3
Lazada	141	47.3
Tiki	66	22.1
TikTok Shop	215	72.1
Other	15	5.0

Source: Results of the authors' analysis based on the survey data.

3.3. Assessment of reliability, convergent validity, and discriminant validity of the measurement scales

In this study, the reliability and validity of the measurement model were evaluated using multiple criteria, including outer loadings, Cronbach's alpha, composite reliability (rhoC), and reliability coefficient rhoA. Convergent validity was assessed through the average variance extracted (AVE), while discriminant validity was examined using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015).

Table 2 reports the results of the measurement model evaluation. The findings indicate that all constructs demonstrate satisfactory internal consistency, with Cronbach's alpha, rhoC, and rhoA values exceeding the recommended threshold of 0.70. Specifically, Cronbach's alpha values range from 0.874 to 0.931, reflecting a high level of reliability across constructs (Hair et al., 2019, 2021). Similarly, rhoC and rhoA values fall within the acceptable

Table 2. Measurement model results.

Variable	Indicator	Loadings	Alpha	rhoA	rhoC	AVE
AI - enabled customer experience (EX)	EX1	0.737	0.895	0.897	0.916	0.577
	EX10	0.774				
	*EX2**	*0.674**				
	EX3	0.741				
	EX4	0.768				
	EX5	0.742				
	EX6	0.757				
	EX7	0.742				
	EX8	0.738				
	*EX9**	*0.683**				
Perceived sacrifice toward AI-enabled services (PS)	PS1	0.850	0.931	0.934	0.946	0.745
	PS2	0.885				
	PS3	0.816				
	PS4	0.909				
	PS5	0.876				
	PS6	0.838				
E-service quality (ESQ)	ESQ1	0.791	0.916	0.918	0.934	0.704
	ESQ2	0.877				
	ESQ3	0.863				
	ESQ4	0.791				
	ESQ5	0.850				
	ESQ6	0.858				
Purchase decision (PD)	PD1	0.833	0.893	0.895	0.921	0.701
	PD2	0.798				
	PD3	0.820				
	PD4	0.863				
	PD5	0.869				
TR: Optimism and Innovativeness (TROI)	TROI1	0.816	0.874	0.904	0.909	0.714
	TROI2	0.804				
	TROI3	0.865				
	TROI4	0.892				
TR: Discomfort and Insecurity (TRDI)	TRDI1	0.880	0.909	0.966	0.935	0.782
	TRDI2	0.851				
	TRDI3	0.909				
	TRDI4	0.896				

*Note: Alpha, rhoC, and rhoA ≥ 0.7 and AVE ≥ 0.5. Observed variables with * Loadings < 0.7 were excluded by the author when establishing the structural model.*

(Source: Results of the authors' analysis based on the survey data).

range, ensuring both lower and upper bounds of composite reliability (Dijkstra & Henseler, 2015; Henseler et al., 2015).

Regarding outer loadings, most observed variables exhibited loadings greater than 0.7, indicating a strong ability to reflect the construct of AI-enabled customer experience. However, two items, EX2 ("AI tools on e-commerce platforms are entertaining") and EX9 ("I feel safe using AI tools on e-commerce platforms"), showed outer loadings below the recommended threshold of 0.7 and were therefore removed during the structural model assessment to improve the reliability and convergent validity of the scale (Hair et al., 2021). From a content perspective, EX2 captures the entertainment aspect of AI services, whereas Vietnamese e-commerce consumers tend to evaluate AI features more in terms of usefulness and efficiency than entertainment value. Similarly, EX9 is more closely associated with perceptions of safety and trust in the system rather than direct experience with AI-enabled services. Therefore, the remaining items still adequately capture the conceptual domain of AI-enabled customer experience, and the removal of EX2 and EX9 did not significantly affect the content validity of the scale.

Convergent validity is confirmed, as all AVE values exceed the threshold of 0.50. Although the AI-enabled customer experience construct reports the lowest AVE (0.577), it remains well above the minimum acceptable level, while the remaining constructs demonstrate strong explanatory power for the variance of their indicators.

Discriminant validity was first assessed using the Fornell-Larcker criterion. As shown in Table 3, the square root of the AVE for each construct (diagonal values) exceeds the corresponding inter-construct correlations, confirming adequate discriminant validity (Fornell & Larcker, 1981).

To further substantiate these results, the HTMT criterion was applied. As reported in Table 4, all HTMT values are below the conservative threshold of 0.85, providing additional evidence that the constructs are empirically distinct (Henseler et al., 2015).

In addition, the authors employed Harman's single-factor test to assess the presence of common method bias (CMB). The results indicated that the first factor accounted for only

Table 3. Assessment of discriminant validity based on the Fornell-Larcker criterion.

	ESQ	EX	PD	PS	TRDI	TROI
ESQ	0.839					
EX	0.609	0.760				
PD	0.671	0.558	0.837			
PS	-0.315	-0.240	-0.260	0.863		
TRDI	0.125	0.003	0.080	0.028	0.884	
TROI	0.053	0.066	0.076	-0.042	-0.020	0.845

Note: The Fornell-Larcker criterion reports the square roots of AVE on the diagonal (in bold) and the correlations among the constructs.

(Source: Results of the authors' analysis based on the survey data).

Table 4. Discriminant validity analysis of the measurement model according to the HTMT criterion.

	ESQ	EX	PD	PS	TRDI	TROI
ESQ						
EX	0.667					
PD	0.737	0.616				
PS	0.336	0.263	0.284			
TRDI	0.126	0.060	0.085	0.067		
TROI	0.066	0.092	0.084	0.065	0.025	

(Source: Results of the authors' analysis based on the survey data).

30.344% of the total variance, which is well below the recommended threshold of 50%. This finding confirms that common method bias was not a significant concern in the study dataset (Cooper et al., 2020).

Multicollinearity was examined using the variance inflation factor (VIF). As shown in Table 5, all VIF values are well below the threshold of 3, with the highest value being 1.669. These results indicate that multicollinearity is not a concern in the structural model and that the estimated path coefficients are not biased by collinearity issues (Hair et al., 2019).

Taken together, the results confirm that the measurement model demonstrates satisfactory reliability, convergent validity, discriminant validity, and absence of multicollinearity, thereby meeting all prerequisites for structural model estimation.

4. Research results

The structural model was estimated using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. Bootstrapping with 5,000 resamples was employed to assess the statistical significance of the path coefficients. The close correspondence between the original estimates and the bootstrap means indicates that the model estimations are stable and robust (Figure 2).

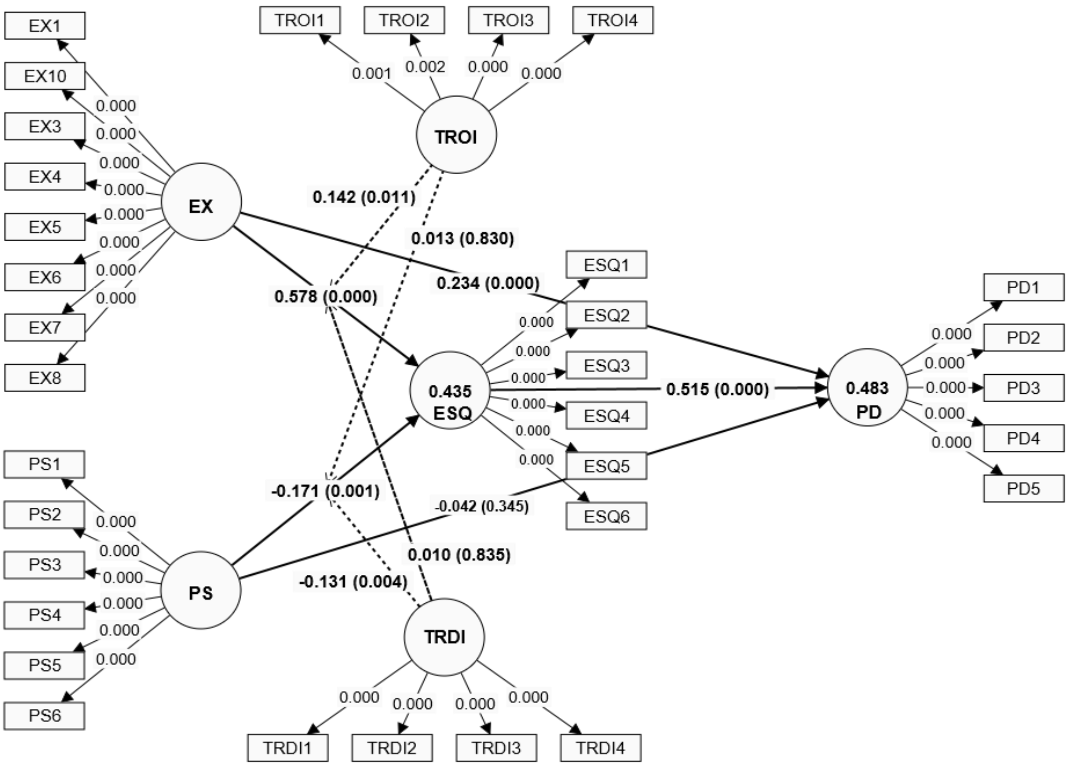

Figure 2. Estimated results of the research model according to PLS-SEM.

(Source: Results of the authors' analysis based on the survey data).

Table 5. Assessment of multicollinearity.

	ESQ	EX	PD	PS	TRDI	TROI
ESQ			1.669			
EX	1.104		1.596			
PD						
PS	1.080		1.114			
TRDI	1.013					
TROI	1.027					

(Source: Results of the authors' analysis based on the survey data).

Table 6 presents the results of the hypotheses testing. The findings reveal that AI-enabled customer experience (EX) has a significant positive effect on purchase decision (PD) (β = 0.234, $p < 0.001$), supporting H1. In contrast, perceived customer sacrifice toward AI (PS) does not exert a significant direct effect on purchase decision (β = -0.042, $p > 0.05$), leading to the rejection of H2. This result suggests that negative perceptions associated with AI do not directly inhibit purchase decisions but may operate through indirect mechanisms.

With respect to mediation effects, e-service quality (ESQ) plays a critical intermediary role. AI-enabled customer experience exerts a positive indirect effect on purchase decision via ESQ (β = 0.298, $p < 0.001$), while perceived customer sacrifice toward AI negatively affects purchase decision through ESQ (β = -0.088, $p < 0.01$). Accordingly, H3 and H4 are supported, highlighting the central role of perceived e-service quality in translating both positive and negative AI-related experiences into purchasing behavior.

Regarding moderation effects, technology readiness exhibits asymmetric moderating influences. Optimism and innovativeness (TROI) positively moderate the relationship between AI-enabled customer experience and e-service quality (β = 0.142, $p < 0.05$), supporting H5a. The moderation plot (Figure 3) indicates that when

Table 6. Hypotheses testing results.

Hypothesis	Relationship	Original sample (O)	T-Value	P-Value	Results ($P<0.05$)
H1	EX → PD	0.234	3.753	0.000	Accepted
H2	*PS → PD*	*-0.042*	*0.945*	*0.345*	*Rejected*
H3	EX → ESQ → PD	0.298	7.757	0.000	Accepted
H4	PS → ESQ → PD	-0.088	3.270	0.001	Accepted
H5a	TROI*EX → ESQ	0.142	2.553	0.011	Accepted
H5b	*TROI*PS → ESQ*	*0.013*	*0.214*	*0.830*	*Rejected*
H6a	TRDI*PS → ESQ	-0.131	2.893	0.004	Accepted
H6b	*TRDI*EX → ESQ*	*0.010*	*0.208*	*0.835*	*Rejected*

Coefficient of determination: ESQ: R^2 = 0.450, AdjR^2 = 0.435 ($p<0.001$); PD: R^2 = 0.488, AdjR^2 = 0.483 ($p<0.001$)

(Source: Results of the authors' analysis based on the survey data).

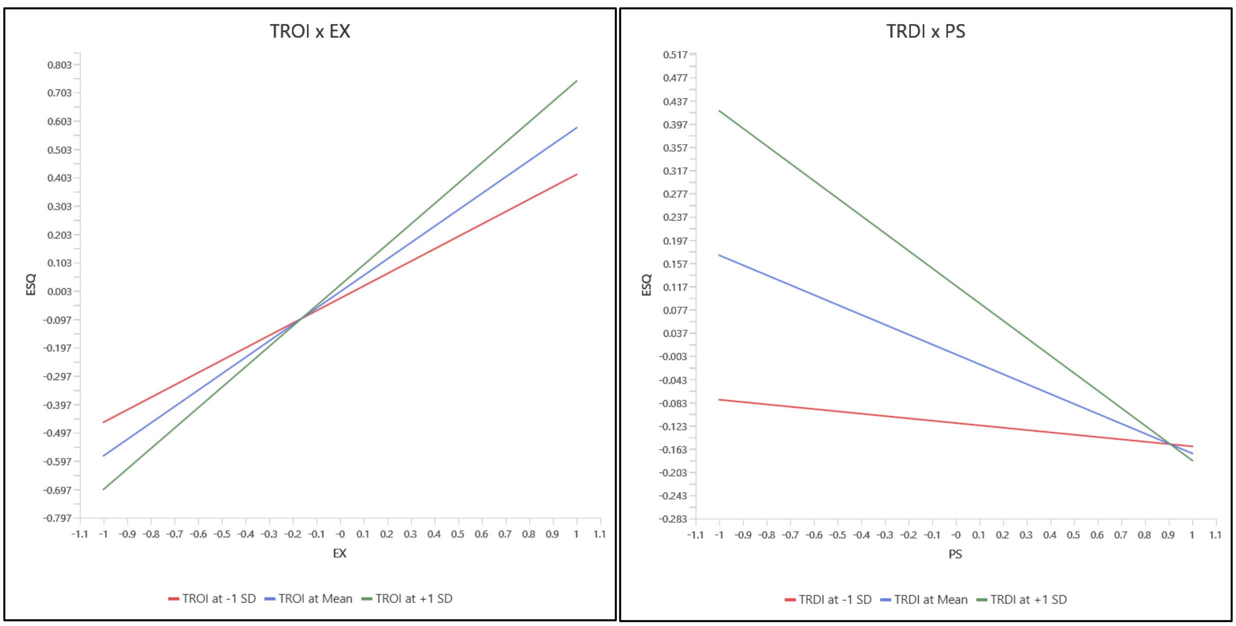

Figure 3. The moderating effect of Technology readiness.
(Source: Results of the authors' analysis based on the survey data).

TROI is high, the EX-ESQ relationship becomes markedly stronger, suggesting that technologically optimistic and innovative consumers are more capable of converting AI-based experiences into favorable quality evaluations. However, TROI does not moderate the relationship between perceived sacrifice and e-service quality, leading to the rejection of H5b.

Conversely, discomfort and insecurity (TRDI) significantly moderate the relationship between perceived customer sacrifice and e-service quality (β = -0.131, $p < 0.01$), supporting H6a. The interaction plot shows that at high levels of TRDI, the negative impact of perceived sacrifice on e-service quality intensifies, whereas this effect is attenuated at lower levels of TRDI. No significant moderation effect of TRDI is found for the relationship between AI-enabled experience and e-service quality, resulting in the rejection of H6b.

The Q^2 predict index was used to assess the predictive relevance of the model, reflecting its out-of-sample predictive capability. A model is considered to have predictive relevance when Q^2 predict values are greater than zero, with higher values indicating stronger predictive power (Hair et al., 2021). As shown in Table 7, both endogenous constructs reported positive Q^2 predict values, specifically ESQ = 0.415 and PD = 0.335, confirming that the model demonstrates good predictive capability.

In terms of explanatory power, the adjusted R^2 value for e-service quality is 0.435, indicating that AI-enabled experience and perceived sacrifice jointly explain 43.5% of the variance in ESQ. The adjusted R^2 value for purchase decision is 0.483, suggesting that the model accounts for 48.3% of the variance in purchasing decisions. These values reflect moderate-to-substantial explanatory and predictive power, consistent with established PLS-SEM benchmarks (Hair et al., 2019).

Overall, the results demonstrate that the impact of AI-enabled services on purchase decisions is not uniform but operates through the mediating role of e-service quality and is contingently shaped by different dimensions of technology readiness. These findings provide robust empirical evidence clarifying the mechanisms through which AI influences consumer behavior in the B2C e-commerce context in Vietnam.

5. Discussion of research findings

5.1. Discussion of direct effects

The findings indicate that AI-enabled customer experience (EX) has a direct and positive effect on customers' online purchasing behavior on B2C e-commerce platforms in Vietnam (β = 0.234; $p < 0.001$). This result is consistent with previous studies suggesting that positive technology experiences enhance perceived usefulness, increase customer engagement, and stimulate online purchasing behavior (Ahmed et al., 2022; Amenuvor et al., 2019; Kumar et al., 2014). In the Vietnamese e-commerce context, where consumers are increasingly familiar with chatbots, recommendation systems, and personalized content, positive AI experiences may enhance convenience, processing speed, and the ability to identify suitable products, thereby encouraging purchasing behavior. This finding reflects the convenience-oriented nature of the Vietnamese e-commerce market, where consumers tend to prioritize convenience and efficiency in online shopping over traditional interactions with sales personnel.

In contrast, perceived sacrifice associated with AI-enabled services (PS) does not have a direct effect on purchasing behavior (β = -0.042; $p > 0.05$). This result suggests that although customers may have concerns related to AI, such

Table 7. Out-of-sample predictive relevance coefficient Q^2.

	Q^2predict	RMSE	MAE
ESQ	0.415	0.771	0.617
PD	0.335	0.825	0.613

(Source: Results of the authors' analysis based on the survey data).

as loss of control, privacy risks, or lack of human interaction, these concerns are not sufficiently strong to directly alter purchasing behavior. In the current Vietnamese e-commerce environment, consumers appear willing to accept a certain level of trade-off in exchange for the convenience, speed, and personalization offered by AI-enabled services. This finding is particularly relevant given that young and frequent online shoppers accounted for a large proportion of the research sample.

5.2. Discussion of the mediating role of electronic service quality

The findings confirm the mediating role of electronic service quality (ESQ) in the relationship between AI-enabled service experience and purchasing behavior ($\beta = 0.298$; $p < 0.001$). This result indicates that AI experiences influence purchasing behavior primarily when they are translated into positive evaluations of electronic service quality. In other words, customers do not respond to AI merely as a technological feature; rather, they respond to the extent to which AI improves information search efficiency, personalization, responsiveness, and convenience throughout the shopping journey. This finding is consistent with the logic of CET and the S-O-R framework, in which AI-enabled service experience functions as the stimulus, ESQ represents the organismic state, and purchasing behavior reflects the behavioral response.

Notably, although perceived sacrifice toward AI does not directly affect purchasing behavior, it exerts a significant negative indirect effect through ESQ ($\beta = -0.088$; $p < 0.01$). This finding is consistent with prior studies suggesting that sacrifice-related perceptions tend to influence behavioral outcomes indirectly through evaluations of value and service quality rather than through immediate behavioral reactions (de Medeiros et al., 2016; Gallarza et al., 2017; Li & Shang, 2020). The result implies that negative perceptions associated with AI primarily reduce customers' evaluations of electronic service quality before influencing purchasing behavior. This may be explained by the characteristics of the Vietnamese e-commerce market, where consumers continue purchasing from familiar platforms due to competitive pricing, diverse service ecosystems, and low switching costs, even when concerns about AI exist. However, such negative perceptions can gradually weaken evaluations of platform reliability, convenience, and service quality, thereby indirectly affecting purchasing behavior in the long term.

5.3. Discussion of the moderating role of technology readiness

The findings reveal that technology readiness (TR) plays an asymmetric moderating role in the relationships between AI experience, perceived sacrifice, and ESQ. Specifically, positive TR dimensions, including optimism and innovativeness (TROI), strengthen the positive effect of AI experience on ESQ ($\beta = 0.142$; $p < 0.05$). This finding suggests that customers with higher levels of technology readiness are more adaptable to AI-enabled services and therefore evaluate electronic service quality more positively. In the Vietnamese context, where substantial differences exist in digital skills and technology experience across consumer groups, the result indicates that AI tends to create greater value for customers who are more familiar with digital environments and more willing to experiment with new technologies.

Conversely, negative TR dimensions, including discomfort and insecurity (TRDI), strengthen the negative effect of perceived sacrifice on ESQ ($\beta = -0.131$; $p < 0.01$). This finding suggests that customers with higher levels of technological anxiety are more sensitive to AI-related risks such as data privacy concerns, lack of transparency, and perceived loss of control during the shopping process. These findings are consistent with prior studies indicating that technology readiness significantly influences how customers evaluate automated and AI-enabled services (Fang et al., 2016; Nguyen et al., 2023; Yang, 2023).

Meanwhile, the remaining moderating relationships (TROI × PS and TRDI × EX) were not statistically significant, suggesting that TR does not uniformly influence all AI-enabled service experiences but rather depends on the nature of the experience and customers' technological characteristics. These findings help explain the inconsistencies in prior studies regarding the effects of AI on customer behavior in e-commerce and further support the argument of the S-O-R framework that consumers' responses to technological stimuli are strongly influenced by individual characteristics.

6. Contributions, limitations, and future research directions

From a theoretical perspective, this study contributes to clarifying the mechanism through which AI-enabled services influence customer purchasing behavior in B2C e-commerce from the perspective of electronic service quality. Unlike prior studies that primarily treated AI as a technological factor or focused on the technical performance of AI systems, this study conceptualizes AI as a component of the digital service environment. The findings demonstrate that positive experiences and perceived sacrifices associated with AI-enabled services can coexist and jointly shape electronic service quality (ESQ). The study therefore extends the ESQ literature in AI-enabled e-commerce contexts while reinforcing the explanatory logic of Customer Experience Theory (CET) and the S-O-R framework by confirming the mediating role of ESQ between AI-enabled service experiences and customer behavioral responses. In addition, the study incorporates technology readiness (TR) as a moderating factor based on the individual difference logic of the S-O-R framework, thereby explaining the heterogeneity in customer responses toward AI-enabled services. The separation of TR into positive and negative dimensions further provides a more nuanced understanding of the moderating mechanism in intelligent service environments.

From a practical perspective, the findings indicate that AI adoption does not automatically generate positive behavioral outcomes unless it is translated into electronic service quality that customers can clearly perceive. Accordingly, e-commerce platforms should position AI as a tool for enhancing customer experience and service quality rather than merely improving operational automation. At the same time, platforms should carefully manage factors that increase customers' perceived sacrifices, particularly those related to data privacy, algorithm transparency, and the availability of human support in complex situations. The findings also suggest that the effectiveness of AI-enabled services depends substantially on customers' levels of technology readiness, implying that e-commerce platforms should segment customers based on their technological adaptability in order to design appropriate levels of automation and personalization.

Despite its contributions, this study has several limitations. First, the survey data were collected primarily from major urban areas in Vietnam, which may limit the generalizability of the findings to other regions. Second, the study did not examine the role of demographic characteristics such as age, income, or digital experience as control or moderating variables. Third, the research focused only on major B2C e-commerce platforms operating in Vietnam. Future studies may extend the analysis to international e-commerce platforms, independent retail websites, or social commerce environments, while also examining additional post-purchase outcomes such as customer loyalty, electronic word-of-mouth, and long-term acceptance of AI-enabled services.

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Contributions of authors

Chien Van Le: conceptualization, methodology, investigation, data curation, and writing – original draft; Trung Kien Pham: formal analysis and visualization; Thang Duc Nguyen: writing – review and editing, and supervision.

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