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AI-Powered Personalization and Purchase Intention on E-Commerce Platforms in Vietnam: An SOR-TAM Based Analysis

Pham Ngoc Khanh*, Lu Thi Ngoc Duyen, Dang Thi Thu Nguyet

Faculty of Business Administration, Industrial University of Ho Chi Minh City, 70000 Ho Chi Minh City, Vietnam

* Correspondence: Pham Ngoc Khanh (phamngockhanh@iuh.edu.vn)

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Abstract: The trend of applying artificial intelligence (AI)-based personalization to e-commerce platforms is becoming increasingly popular to attract customers to buy products and services. To contribute to explaining this, this study was conducted to analyze the impact of artificial intelligence-based personalization on customers' purchase intention when shopping on e-commerce platforms in Vietnam. Based on the PLS-SEM analysis method with valid data collected from 400 survey questionnaires for people who have shopped on e-commerce platforms. The results show that innovation, system quality, and information quality positively affect perceived usefulness and trust, thereby promoting purchase intentions. In addition, immersive experiences also positively affect purchase intentions. On that basis, the authors propose some management implications to help businesses operating on e-commerce platforms better understand the impact of AI-based personalization on purchase intentions, thereby being able to build strategies to improve operational efficiency and increase profits.

Keywords: Personalization; AI; SOR model; Purchase intention; AI-based personalization

JEL Classification: D12, O33, L86

1. Introduction

According to a report from MarketingAI (2024), despite the challenges facing the global economy, Vietnam's e-commerce market still maintains significant growth. The Bain & Company (2023) recorded an 11% growth rate of Vietnam's e-commerce in the period 2022–2023. The report also predicted that the compound annual growth rate (CAGR) will reach 22% and the industry's total merchandise value could reach 24 billion USD by 2025. Along with that, according to Advertising Vietnam (2024), the 2024 overview report on the online retail market and the 2025 forecast, the total revenue of the five major e-commerce platforms in Vietnam including Shopee, Lazada, TikTok Shop, Tiki, and Sendo reached about 318.9 trillion VND in 2024, an increase of 37.36% compared to 2023. This figure shows the rapid expansion and strong growth potential of e-commerce in the Vietnamese market in the coming period. In the context of increasingly fierce competition between e-commerce platforms in the Vietnamese market, enhancing customer experience personalization is becoming a leading strategy to create a competitive advantage. According to a survey by Accenture (2024), 91% of consumers said they tend to buy more from brands that provide personalized recommendations and offers. Also, according to McKinsey & Company (2024), 78% of consumers tend to recommend brands that apply personalization, which encourages them to return to shop more often. The above figures show that personalization is not only a trend but also an important factor helping businesses grow sustainably and increase customer purchase intentions. More and more businesses are integrating AI into their operations to improve customer personalization experiences. In Vietnam, according to Statista (2025), the AI market is expected to reach 1.3 billion USD by 2025, with great potential in e-commerce and digital marketing. A report by Bain & Company predicts that by 2025, about 80% of businesses in Vietnam will use AI to improve operational efficiency and enhance customer experience personalization. Platforms such as Tiki, Shopee, and Lazada have quickly applied AI to analyze user behavior and personalize experiences. According to Accesstrade Vietnam (2025), a report on Affiliate Marketing, Shopee is one of the typical businesses in strongly applying AI to deploy personalized product recommendation features. Thanks to that, the platform's average revenue has grown by 15% in 2024, reflecting the positive impact of AI personalization on business results.

In addition, the impact of personalization on consumers, especially when supported by AI on e-commerce platforms, has become the focus of many international studies in recent years. Ballı (2024) asserted that AI-based product personalization has a positive impact on purchase intention, satisfaction, and brand loyalty. Yin et al. (2025) demonstrated that AI-based personalized product recommendations increase click-through intention through immersive experiences and technology acceptance. Lu & Kim (2023) pointed out that personalized recommendation systems enhance trust and perceived usefulness, thereby increasing purchase intention. El Alam & Bitar (2024) emphasized trust, usefulness, interactivity, and ease of use in driving purchase intention through personalized AI recommendations. Similarly, Pognonec & Bornard (2023) pointed out that AI contributes to improving purchase intention in the cosmetics industry due to convenience. In Vietnam, the number of studies on the impact of AI-based personalization on purchase intention is limited. Current studies mainly focus on the general role of personalization, without analyzing each component such as system quality, information quality or innovation as shown in the study by Chi & Anh (2024). This gap makes it difficult for businesses to build a personalization strategy that suits the needs of Vietnamese consumers. Therefore, the research team: "AI-Powered Personalization and Purchase Intention on E-Commerce Platforms in Vietnam: An SOR-TAM Based Analysis" with the aim of clarifying the impact of AI-based personalization on purchase intentions, thereby proposing managerial implications to help businesses improve the effectiveness of personalization strategies and promote customers' purchase intentions.

2. Theoretical Basis and Research Hypotheses

2.1 Related Theories

Technology Acceptance Model (TAM): TAM is an important theoretical framework in analyzing the level of user acceptance of new technologies, especially in the field of e-commerce with AI applications. TAM focuses on analyzing technology acceptance behavior at the individual level, different from the UTAUT model commonly applied in organizational environments (Rondán-Cataluña et al., 2015). In this study, the authors apply the TAM model to explain how external factors such as innovation and information quality influence customers' perceived usefulness, which in turn affects their purchase intention. The application of TAM not only helps to clarify the process of consumers accepting AI technology on e-commerce platforms, but also provides a solid scientific basis for evaluating the effectiveness of AI-based personalized recommendation systems in promoting shopping behavior.

Stimulus-Organism-Response (SOR) theoretical model: The SOR model was developed by Mehrabian & Russell (1974), based on environmental psychology. According to this model, external factors act as stimuli, creating certain cognitive or emotional responses within people, thereby influencing their behavior (Jacoby, 2002). In the field of consumer behavior research, the SOR model has become the theoretical foundation for related studies on online shopping (Li et al., 2022). In this study, the authors apply the SOR model as a theoretical foundation to build and analyze the relationships in the proposed research model. Specifically, based on the SOR model, information quality and system quality are considered external stimuli, affecting internal psychological factors such as perceived usefulness, trust, and consumer immersion. These internal factors affect purchase intention, i.e. consumer behavioral response on e-commerce platforms.

2.2 Related Concepts

AI

AI is a term coined by John McCarthy at the Dartmouth Conference in 1956, defined as the field of science and engineering aimed at developing intelligent thinking machines and computer programs (Arslan, 2020). AI brings significant improvements, from personalizing product recommendations, optimizing real-time pricing, predicting consumer demand, improving smart search to improving supply chain and logistics efficiency (Bawack et al., 2022). By harnessing the power of AI, businesses can analyze customer data more deeply, make quick decisions, and automate many important processes, leading to improved operational efficiency and a more engaging shopping experience (Bawack et al., 2022).

Personalization

In marketing, personalization is understood as a customer-oriented strategy, aiming to deliver the right message to the right person at the right time (Dangi & Malik, 2017). The growing interest in personalization in the research community stems from the widespread use of the Internet (Montgomery & Smith, 2009) and the development of e-commerce (Dangi & Malik, 2017). However, personalization is not a new concept and has existed since the days of traditional commerce, when salespeople tailored their service based on each customer (Vesanen, 2007). There are many different definitions of personalization. Some focus on the web experience, others emphasize tailoring products and services to customer behavior or creating value for customers (Montgomery & Smith, 2009). In this study, personalization is understood according to Imhoff et al. (2001) as the ability of a business to recognize customers as individuals and provide appropriate messages, offers, and products or services.

AI-Based Personalization in E-Commerce

Gao & Liu (2022)'s study focuses on the role of AI in interactive marketing personalization, with elements such as customer profiling, behavioral instigation, and experience navigation to maintain engagement throughout the customer journey. AI is expected to have a strong impact on personalization in marketing (Paschen et al., 2019). In this study, AI-based personalization will be explored through recommender systems (RS), a technology that suggests products based on customers' unique needs and preferences. RS are one of the most important and popular applications of personalization powered by artificial intelligence (Zanker et al., 2019). RS helps users easily access relevant products and content through suggestions based on personal preferences. The goal of recommender systems is to provide personalized products and services that more accurately meet customers' needs and expectations (Singh et al., 2019).

According to Alhijawi et al. (2022), three important indicators to evaluate the effectiveness of recommender systems include: system quality, information quality, and innovation. System quality is reflected in the accuracy and diversity of recommendations (Panniello et al., 2016). In which, accuracy represents the degree of relevance to user preferences (Herlocker et al., 2004), while diversity reflects the differences between recommended products (Park & Han, 2013). Information quality is related to the persuasiveness and completeness of recommendation content (Mukherjee & Nath, 2007; Yang, 2020). Persuasiveness is the extent to which the suggested content helps consumers feel confident and convinced to consider products (Yang, 2020), while completeness reflects the extent to which the information provided is comprehensive and detailed (Mukherjee & Nath, 2007). Meanwhile, innovativeness represents the ability of the system to provide novel suggestions that are different from the user's previous experience (Castells et al., 2021). Some studies have shown that although system quality, information quality, and innovativeness are not the only aspects of recommender systems, they are three fundamental factors that reflect the effectiveness of personalized recommender systems (Castells et al., 2021).

E-Commerce

E-commerce is the buying, selling, and exchanging of goods and services over the Internet, using digital devices such as smartphones, tablets, or personal computers (Faqih & Jaradat, 2015; García & Margallo, 2014; Jalilvand & Samiei, 2012; Tavera & Londoño, 2014). According to Bloomenthal (2021), this concept includes various forms such as retail, wholesale, dropshipping, crowdfunding, digital or physical product offerings, and subscription services... Due to its diversity and accessibility, e-commerce becomes attractive to consumers. In addition, e-commerce platforms not only benefit end users but also help businesses effectively exploit analytical tools to optimize business operations (Tran, 2021). On the customer side, this form brings many benefits such as detailed product information, rich selection of categories, transparency between suppliers, and competitive prices (Reinartz et al., 2019).

Purchase Intention

Purchase intention is defined as the willingness to pay as well as the attitude and tendency of consumers towards purchasing a certain product or service (Bhagat et al., 2023). In e-commerce, purchase intention is a predictor of actual behavior, reflecting the link between behavioral intention and shopping behavior (Kim et al., 2008). The stronger the consumer's purchase intention, the more likely they are to make a decision to buy or use the product or service. Many factors influence purchase intention, including multichannel advertising (Lin, 2011), direct and online word-of-mouth (Jalilvand & Samiei, 2012), brand loyalty and trust (Büyükdağ, 2021), brand equity (Senthilnathan & Tharmi, 2012), product attitudes, and social norms (Ajzen, 1980).

Based on the S-O-R theoretical model and previous related studies on purchase intention, the author proposes a research model as shown in Figure 1.

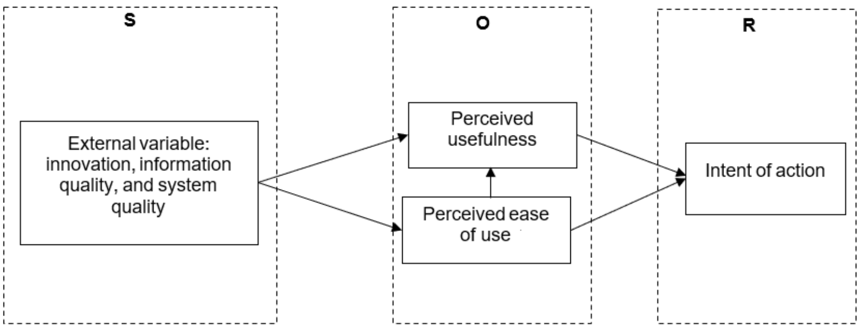

Figure 1. Summary diagram of basic theory

2.3 Research Hypothesis

2.3.1 Innovation

According to Castells et al. (2021), innovation is the extent to which a shopping experience differs from prior ones in order to pique interest and customize the encounter. Users would quickly become disinterested if AI merely makes product recommendations based on outdated practices without any innovation. According to Herlocker et al. (2004), a recommendation system should not only be accurate but also focus on novelty, surprise and the ability to discover products that users have not been exposed to before. Similarly, Zhang & Tao (2012) also asserted that innovativeness in recommendations plays a positive role in enhancing the perception of the system's usefulness. In addition, according to Knijnenburg et al. (2012), when the recommender system suggests innovative products, it will not only satisfy the need for discovery but also make consumers perceive that the product recommendation system is really useful because it understands them. From there, the author proposes the hypothesis:

Hypothesis H1: Innovation has a positive impact on customers' perceived usefulness when shopping on e-commerce platforms.

2.3.2 Information quality

The relevance, correctness, completeness, timeliness, and usefulness of information in relation to its intended purpose are all measured by its quality. Good information saves time by assisting users in making precise and useful judgments. The degree to which consumers can use information to assess a product, brand, or company is known as information quality (Gao et al., 2012). As a result, customers can make more informed decisions about important aspects or attributes of a product or service (Chiu et al., 2005). Information quality is often divided into two main factors: persuasiveness and completeness (Luo et al., 2013; Yang, 2020). In the context of personalized recommender systems, information quality becomes even more important in building users' trust in product recommendations (Cremonesi et al., 2012). According to Yang (2021), perceived information quality has a positive impact on trust in recommendations. From there, the author proposes the hypothesis:

Hypothesis H2: Information quality has a positive impact on customers' perceived usefulness when shopping on e-commerce platforms.

Hypothesis H3: Information quality has a positive impact on customers' trust when shopping on e-commerce platforms.

2.3.3 System quality

System quality relates to the reliability, accuracy, and completeness of the information collected and processed within the system, directly affecting the organization's decisions and operational efficiency. According to Lu & Kim (2023), system quality is the extent to which a system can meet users' expectations in terms of performance, reliability, and ability to provide content that is relevant to their needs. System quality is assessed based on two main factors: variety and accuracy (Panniello et al., 2016; Roudposhti et al., 2018). Pu et al. (2011) showed that users' perceptions of variety have a positive influence on their trust in the system and their behavioral intentions. Similarly, Panniello et al. (2016) also emphasized that the accuracy and diversity in context-based recommender systems have an impact on consumer trust, which in turn affects the number of products they purchase as well as their spending level. From there, the author proposes the hypothesis:

Hypothesis H4: System quality has a positive impact on customer trust when shopping on e-commerce platforms.

2.3.4 Immersion experience

Immersion experience in online environments is described by Hoffman & Novak (1996) as a state where the user is completely detached from the real world and completely focused on the activity being participated in. With the development of AI, the immersion experience in e-commerce is increasingly expanding. Yin et al. (2025) defined this as a state when consumers feel deeply present and fully focused on the process of interacting with a personalized recommendation system. Liao et al. (2023) pointed out that immersive experiences can affect purchase intentions, as consumers tend to spend more time learning about products, thereby increasing purchase intentions. From there, the author proposes the hypothesis:

Hypothesis H5: Immersive experiences have a positive influence on customers' purchase intentions when shopping on e-commerce platforms.

2.3.5 Perceived usefulness

Davis (1989) perceived usefulness is the extent to which users believe that using a particular system can improve their job performance. Customers' opinions about the usefulness of recommender systems, especially when they perceive these systems to be accurate and efficient, significantly influence their purchase intentions. Similarly, Zhao & Wang (2020) also concluded that perceived usefulness has a positive impact on purchase intention. Overall, these findings highlight the important role of perceived usefulness in how AI-powered personalized recommendations can drive purchase intention. Therefore, the author proposes the following hypothesis:

Hypothesis H6: Perceived usefulness has a positive impact on customers' purchase intention when shopping on e-commerce platforms.

2.3.6 Trust

According to Pognonec & Bornard (2023), trust is understood as the degree of consumer willingness to believe that a product can perform the promised function. Lu & Kim (2023) assert that, if the products recommended by the online shopping platform system always satisfy customers and are reliable, consumers will increasingly trust the recommended products and as trust increases, they will be willing to pay more for the products, which will further affect consumers' purchase intentions. From there, the author proposes the hypothesis:

Hypothesis H7: Trust has a positive influence on customers' purchase intention when shopping on e-commerce platforms.

2.3.7 Mediating role of perceived usefulness and trust

In order to shed light on the role of mediating elements in the relationship between AI-based personalization and customers' buy intention when shopping on e-commerce platforms, the author puts up the following mediating hypotheses, which are based on the relationships established in the preceding hypotheses:

Hypothesis H8: Based on hypotheses H1 and H6, innovation has a positive impact on consumers' purchase intentions when they buy on e-commerce platforms through the mediating role of perceived utility.

Hypothesis H9: Based on hypotheses H2 and H6, information quality has a positive impact on consumers' purchase intentions when they buy on e-commerce platforms through the mediating role of perceived utility.

Hypothesis H10: Based on hypotheses H3 and H7, information quality has a positive impact on consumers' purchase intentions when they buy on e-commerce platforms through the mediating role of trust.

Hypothesis H11: Based on hypotheses H4 and H7, system quality has a positive impact on consumers' purchase intentions when they buy on e-commerce platforms through the mediating role of trust.

The author suggests the following model (Figure 2) based on the literature study of the state of the field, pertinent theories, and the unique traits of online shoppers on e-commerce platforms.

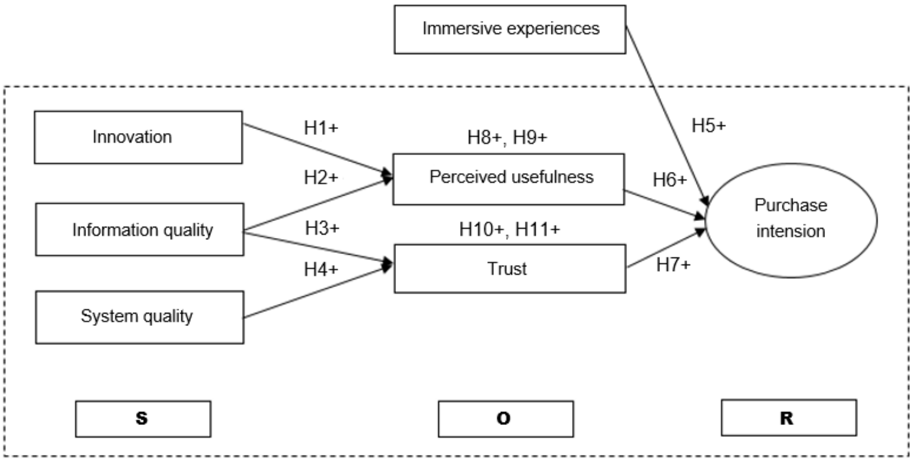

Figure 2. Proposed research model

3. Research Methodology

Research method: The study uses a combination of qualitative and quantitative research methods, divided into 4 stages. In stage 1, the authors collected and analyzed documents to build a theoretical basis and propose a research model. In stage 2, the group conducted qualitative research, prepared a scale table and interviewed 10 experts. In stage 3, the group conducted preliminary quantitative research, collected data from 50 people to test the reliability of the scale with Cronbach's Alpha. In stage 4, conducted official quantitative research with 400 valid survey forms, then used SPSS and SmartPLS software to analyze the data.

Research scales: The scales utilized are derived from scales from earlier research, with the phrasing modified to fit the research topic and environment. In particular, the five observed variables of the Innovation scale (SDM) were taken from the studies of Pognonec & Bornard (2023) and Zhao et al. (2025). Six observable factors are included in both the System Quality (CLHT) and Information Quality (CLTT) scales, which are derived from Lu & Kim (2023). Four observed variables for the Immersive Experience scale (TNDC) were taken from Yin et al. (2025). The four observed factors that make up the Perceived Usefulness scale (SHI) were taken from Pognonec

& Bornard (2023). Three observed factors that were taken from El Alam & Bitar (2024) and Lu & Kim (2023) make up the Trust scale (LT). Finally, the Intention scale (YD) in Table A2 is made up of three observable variables that were taken from Lu & Kim (2023).

Sample size and data collection method: According to Trong & Ngoc (2008), the minimum sample size for factor analysis needs to be at least 5 times the number of observed variables. At the same time, according to the formula of Tabachnick & Ullman (2007), with 4 independent variables, the minimum sample size in regression analysis is N = 8 * 4 + 50 = 82. However, to increase reliability and reduce errors in quantitative research, the authors decided to survey 470 consumers who have been shopping on e-commerce platforms in provinces and cities of Vietnam to ensure geographical balance. Of the 470 survey forms distributed, 456 responses were received; after eliminating 56 invalid forms, 400 valid forms remained for analysis.

Data analysis method: Using descriptive statistics method through SPSS 26 software to summarize and present basic demographic characteristics of the data set collected from the survey. In addition, using PLS-SEM analysis method through SmartPLS software to evaluate the measurement model and structural model. To evaluate the measurement model, the study used an external loading factor of 0.7 (Fong & Law, 2014), Cronbach's Alpha coefficient greater than 0.7 (Fink & Litwin, 1995), AVE greater than 0.5 (Fong & Law, 2014), composite reliability (CR) greater than 0.7 (Hair Jr et al., 2017) and HTMT index less than 0.85 (Henseler et al., 2015). Next, the study will evaluate the structural model based on the assessment of multicollinearity issues with VIF index less than 3 (Fong & Law, 2014) and the significance of the impact relationships in the model with p-value < 0.05 (Vinzi et al., 2010).

4. Research Results

4.1. Demographic Factor Statistics

Among a total of 400 valid survey responses, there were 146 males (accounting for 36.5%) and 254 females (accounting for 63.5%). In terms of age, the group aged from 18 to under 25 years accounted for 67.3%, followed by the group aged from 25 to under 35 years at 15.5%, the group aged from 35 to under 45 years at 7.8%, those under 18 years at 6.3%, and those aged 45 years and above at 3.3%. Regarding occupation, students made up 57.8%, office workers represented 18.3%, other occupations (9.5%), school students (6.3%), civil service employees (5.5%), and entrepreneurs (2.8%). Meanwhile, 88.3% of the respondents possessed a higher level of education, and 11.8% had a lower level of education. In terms of living area, 53.5% of respondents currently live in urban areas, and 46.5% live in suburban areas. Considering shopping frequency, the group shopping 3–4 times a month accounted for the highest percentage at 64%, 17% shop 1–2 times a month, 10.8% shop 5–10 times a month, and 8.3% have other frequencies. In addition, the most common income ranges from 1 million to under 5 million VND, accounting for 54.3%, from 5 to under 10 million accounting for 26%, under 1 million VND accounting for 10.5%, and from 10 million and above accounting for 9.3%.

4.2 Model Measurement Validation

The scales' convergent validity and reliability are used to assess the measurement model. The composite reliability (CR) is between 0.865 and 0.900, and the Cronbach's Alpha (CA) coefficient is between 0.766 and 0.867. Since every value is above the 0.7 criterion, both indices show that the measurement scale achieves dependability. The average variance extracted (AVE) values, which range from 0.586 to 0.683, are all higher than the necessary threshold of 0.5. The minimal level is exceeded by all factor loading values, which range from 0.728 to 0.846 (Hair Jr et al., 2017). Therefore, all 7 scales in this study achieve convergent validity as shown in Table 1.

Table 1. Results of reliability and convergent validity analysis

Scale	Factor Loadings	CA	CR	AVE
Innovation (SDM)	0.731–0.805	0.830	0.880	0.595
Information quality (CLTT)	0.754–0.795	0.859	0.895	0.586
System quality (CLHT)	0.728–0.802	0.867	0.900	0.601
Inmmersive experiences (TNDC)	0.785–0.839	0.817	0.879	0.646
Perceived usefulness (SHI)	0.723–0.824	0.806	0.872	0.632
Trust (LT)	0.808–0.846	0.766	0.865	0.681
Purchase intention (YD)	0.795–0.854	0.769	0.867	0.684

The Heterotrait-Monotrait (HTMT) correlation index is applied to measure the discriminant validity of outcome-type scales, and the HTMT index between pairs of variables being less than 0.85 indicates that the measurement model achieves discriminant validity (Henseler et al., 2015). In Table 2, the results regarding the discriminant validity of the scales show that the HTMT indices between pairs of variables are all less than the threshold of 0.85, thus the outcome-type scales in the model achieve discriminant validity.

Table 2. HTMT index analysis results

Scale	CLHT	CLTT	LT	SDM	SHI	TNDC
CLHT						
CLTT	0.593					
LT	0.510	0.635				
SDM	0.457	0.426	0.449			
SHI	0.427	0.540	0.421	0.339		
TNDC	0.538	0.496	0.419	0.398	0.388	
YD	0.739	0.778	0.737	0.620	0.646	0.685

4.3. Structural Model Assessment

Assessing multicollinearity

According to Hair Jr et al. (2017), the assessment of multicollinearity among the variables in the model is done through the variance inflation factor (VIF). From Table 3, all variables have VIF values < 3. It can be concluded that there is no multicollinearity among the observed variables in the model.

Table 3. Results of the collinearity analysis

Scale	CLHT	CLTT	LT	SDM	SHI	TNDC	YD
SHI		1.148		1.148			1.196
LT	1.354	1.354					
YD			1.205			1.193	

Assessing of R^2 values

The analysis results in Table 4 show that the adjusted R^2 value of "Trust" is 0.299. This means that the independent variables in the model can explain 29.9% of the variance in the variable "Trust". The remaining 70.1% is due to system errors and exogenous factors not included in the model. Similarly, when considering "Perceived Usefulness", the adjusted R^2 value is 0.221. This indicates that the independent variables explain 22.1% of the variance of this variable. The remaining 77.9% is due to system errors and other factors beyond the scope of the study model. The variable "Purchase Intention" has an adjusted R^2 value of 0.532, indicating that 53.2% of the variance in "Purchase Intention" is explained by the two factors "Trust" and "Perceived Usefulness". The remaining 46.8% can be explained by system errors and other factors not included in the model.

Table 4. Analysis results of the R^2

Variables	R^2	Adjusted R^2
LT	0.302	0.299
SHI	0.225	0.221
YD	0.535	0.532

Assessing the f-squared coefficient

The strength of an independent variable's influence on a dependent variable is shown by the f^2 coefficient. Small, medium, and large f^2 values are defined as 0.02, 0.15, and 0.35, respectively. The independent variable is thought to have no effect on the dependent variable if the f^2 value is less than 0.02. With the exception of the independent variable "Innovation" (0.02), which has a little impact on the dependent variable "Perceived Usefulness", the results indicate that all independent variables have a moderate impact on the dependent variables in Table 5.

Table 5. Analysis results of the f^2 coefficient

Variables	CLHT	CLTT	LT	SDM	SHI	TNDC	YD
CLHT			0.047				
CLTT			0.179		0.188		
LT							0.228
SDM					0.020		
SHI							0.154
TNDC							0.199
YD							

Research hypothesis testing results

The research results in Table 6 show that the p-values of the hypotheses are all less than 5%, and the effect coefficients are all greater than 0, indicating that Immersion Experience, Perceived Usefulness, and Trust all have a positive impact on Purchase Intention, with effect coefficients of 0.332, 0.292, and 0.357 respectively. Additionally, Innovation and Information Quality also positively impact Perceived Usefulness, with standardized regression coefficients of 0.134 and 0.409 respectively. Information Quality (0.411) and System Quality (0.211) also positively affect Trust.

Table 6. Research hypothesis testing results

Hypothesis	Relationship	Standardized Regression Coefficient	*t*-test	*p*-value	Conclusion
H1	SDM → SHI	0.134	2.809	0.005	Supported
H2	CLTT → SHI	0.409	9.246	0.000	Supported
H3	CLTT → LT	0.411	8.783	0.000	Supported
H4	CLHT → LT	0.211	4.371	0.000	Supported
H5	TNDC → YD	0.332	8.767	0.000	Supported
H6	SHI → YD	0.292	7.253	0.000	Supported
H7	LT → YD	0.357	10.190	0.000	Supported

Results of testing indirect relationship

The results in Table 7 indicate that all intermediary relationships in the research model achieved statistical significance and are accepted, as all p-values are less than 0.05. This indicates that independent variables have a significant impact on the dependent variable through their corresponding intermediary variables.

Table 7. Results of the separate mediation variable test

Relationship	Standardized Regression Coefficient	Sample Mean	Standard Deviation	*t*-test	*p*-value
CLTT → SHI → YD	0.120	0.119	0.022	5.396	0.000
CLHT → LT → YD	0.075	0.077	0.019	3.997	0.000
CLTT → LT → YD	0.147	0.147	0.024	6.006	0.000
SDM → SHI → YD	0.039	0.041	0.016	2.465	0.014

The research results show that perceived usefulness is a partial intermediary in the relationship between innovation (0.039) and information quality (0.120) affecting purchase intention. Similarly, trust is a partial intermediary in the relationship between information quality (0.147) and system quality (0.075). These results indicate the positive influence of independent variables on the dependent variable through the intermediary variable, supporting the acceptance of research hypotheses H8+, H9+, H10+, and H11+.

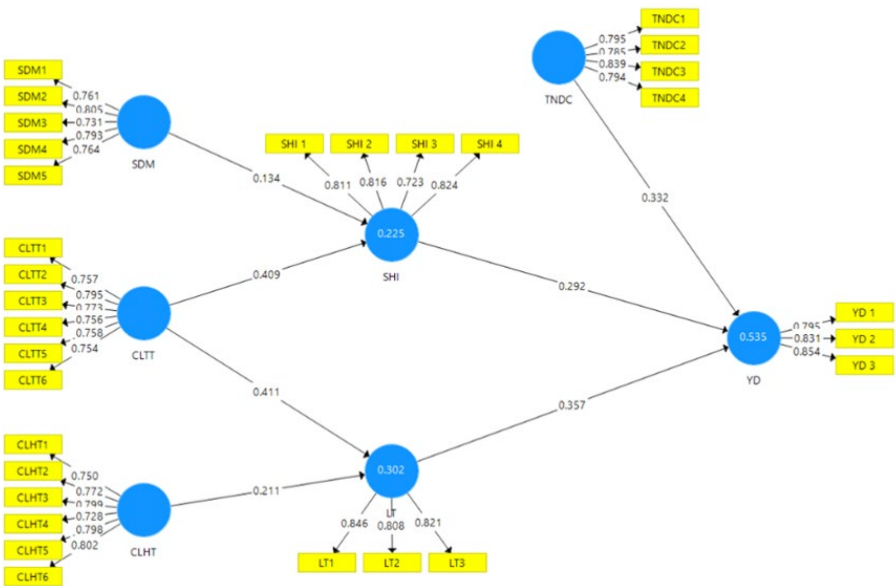

Figure 3. Results of the PLS-SEM model analysis

Results of SEM model analysis

The structural model regarding the relationship between the factors of AI-based personalization affecting customers' purchase intentions when shopping on e-commerce platforms is shown in Figure 3. The model indicates that the R-squared value for the purchase intention factor is 0.535. This means that 53.5% of the variance of this factor is explained by the two factors of "Trust" and "Perceived Usefulness".

4.4 Discussion

When comparing the research results of this study with previous studies, the authors found a clear similarity. Specifically, the factors proposed by the group in the model all have a positive impact on purchase intention. Hypothesis H1 suggests that "Innovation" positively affects "Perceived Usefulness", and the test results accepted this hypothesis with a standardized regression coefficient of 0.134, which is similar to the previous research by Pognonec & Bornard (2023). However, the impact level of "Innovation" on consumers' "Perceived Usefulness" in this group's research is lower than in the previous study, with a coefficient $\beta = 0.362$, which may be due to differences in the research subjects or the specific research context, such as products, industries, or business areas that are characterized by personal experience, consumer needs, and frequently changing market trends etc. Hypotheses H2 and H3 indicate that "Information Quality" positively affects both "Perceived Usefulness" and "Trust", with standardized regression coefficients of 0.409 and 0.411, respectively. These results are consistent with the research conducted by Lu & Kim (2023). However, unlike the study by Lu & Kim (2023), which surveyed a group of consumers using various online shopping platforms in South Korea, the authors carried out their survey on users of e-commerce platforms in Vietnam, aiming to further analyze the behavior and factors influencing specific purchase intentions. Hypothesis H4 shows that "System Quality" positively affects "Trust", with a standardized regression coefficient of 0.211. This research result is also consistent with the findings of Lu & Kim (2023). Hypothesis H5 suggests that "Immersive Experience" has a positive impact on "Purchase Intention", with a standardized regression coefficient of 0.322, similar to the study by Yin et al. (2025).

However, the notable difference is that in the study by Yin et al. (2025), the factor of "Immersive Experience" was identified as a mediating variable, serving as a bridge between "Personalized Experiences" and "Purchase Intention". Unlike previous research, the new findings in this study have broadened the perspective by demonstrating that "Immersive Experience" is not only a mediating variable but also directly influences "Purchase Intention". Hypothesis H6 indicates that "Perceived Usefulness" positively affects "Purchase Intention", with a standardized regression coefficient of 0.292. The results of this study are consistent with the research results of El Alam & Bitar (2024), Lu & Kim (2023), and Pognonec & Bornard (2023). This further reinforces the view that "Perceived Usefulness" is an important factor in forming "Purchase Intention" in the e-commerce environment. Hypothesis H7 shows that "Trust" has a positive impact on "Purchase Intention", with a standardized regression coefficient of 0.357. This finding is also entirely consistent with the research results of Lu & Kim (2023), as both studies emphasize the importance of trust in driving purchase intentions in the e-commerce environment.

5. Conclusion and Implications

5.1 Conclusion

Through the application of the SOR model, the study has obtained significant results with high practical value. Specifically, the group of authors has identified the core factors of AI-based personalization that affect purchase intention and measured the impact level of each factor in the context of consumers shopping on e-commerce platforms. The results show that three main factors affect purchase intentions: trust, immersive experience, and perceived usefulness. Among them, trust plays a dominant role, reflecting consumers' confidence in personalized products as a key factor driving shopping behavior. The immersive experience helps enhance emotional attachment to the platform, while perceived usefulness reflects the extent to which personalized products meet users' real needs.

In addition, while system quality and innovation also have an impact, albeit to a lesser degree, individualized characteristics like information quality are found to be important determinants in fostering trust and improving sense of utility. Additionally, the study highlights how trust and utility perception play a mediating role in converting individualized factors into purchase intention. The study has made substantial contributions to the scientific understanding and practical implementation of AI-based personalization for e-commerce platforms. Based on these findings, the research has suggested management implications to improve platform operational efficiency, improve user experience quality, and thereby increase customers' purchase intention when shopping on e-commerce platforms. From a scientific perspective, the research contributes to the refinement of the theoretical basis regarding the impact of AI in e-commerce, while also expanding the SOR model of Lu & Kim by integrating the factor of "Innovation" and harnessing "Immersive Experience" as an independent variable. These additions make the theoretical model more comprehensive while also opening up a new perspective on how consumers react to personalized proposals. From a practical standpoint, the research provides important foundations to help e-commerce businesses better understand the factors driving customers' purchasing intentions, thereby enabling them to develop effective personalization strategies, enhance user experiences, and increase competitiveness in the market.

5.2 Implications

5.2.1 Regarding information quality

Research shows that "Information Quality" has the strongest impact on trust and the perceived usefulness of personalized recommendations on e-commerce platforms, with standardized regression coefficients of 0.411 and 0.409, respectively. The observed variables related to information quality have average values ranging from 3.19 to 3.29, indicating a neutral assessment from customers. Platforms can use AI to create automated content moderation systems to enhance the quality of information by swiftly identifying mistakes like typos, inadequate descriptions, or improper photos. This will automatically filter and restrict the presentation of inferior products. Improve machine learning algorithms to gather, process, and evaluate search history, customer feedback, and shopping behavior data to produce thorough suggestions that cater to each customer's needs. In addition, making the AI-based recommendation mechanism transparent by implementing simple explanation features for the reasons behind recommendations, such as "You viewed product A, so you might like product B", to increase trust and customer satisfaction with the system. Moreover, natural language processing (NLP) technology can be used by platforms to automatically create or modify product descriptions, guaranteeing clients clear, thorough, SEO-friendly, and easily comprehensible information.

5.2.2 Regarding system quality

The factor "System Quality" has a positive impact on users' "Trust", with a standardized regression coefficient of 0.211. Users rated the quality of the system quite evenly, with an average value ranging from 3.26 to 3.38. To improve system quality, it is necessary to focus on enhancing the accuracy of the product recommendation system. Specifically, AI can be applied to conduct deeper semantic analysis when users search using text, helping to correctly understand the intent and context of the queries, thereby providing more accurate recommendations. With image search, the computer vision system can identify detailed characteristics of products such as style, color, material, etc., and compare them with available product data to suggest similar options. In addition, the integration of voice recognition technology will make it easier for users to search, especially on mobile devices, while AI will learn to interpret diverse voice commands to provide appropriate suggestions. To expand diversity, AI can be leveraged to recommend complementary or alternative products from different categories and brands, while still being relevant to the user's needs, thereby stimulating exploration and increasing order value. At the same time, a reinforcement learning system should be implemented so that the recommendation system continuously learns from user responses, self-adjusting its model to provide increasingly accurate suggestions.

5.2.3 Regarding innovation

The factor "Innovation" plays an important role in shaping perceptions of the usefulness of personalized recommendations for users on e-commerce platforms. Specifically, the standardized regression coefficient of 0.134 indicates a significant influence of this factor. E-commerce platforms need to enhance the personalized experience by analyzing users' current shopping behavior to identify gaps, that is, products that they have never searched for or purchased but may be interested in. In addition, it is necessary to implement highly exploratory suggestion functions, such as random recommendations based on personal preferences (color, price range, style, etc.), which will help users not to be limited to familiar products but have the opportunity to access new and unique items, stimulating interest and unexpected consumption behavior. There should be a focus on integrating community power into the product suggestion system. Instead of personalizing solely based on individual user data, the system should analyze behavior, trends, and evaluations from user groups with similar characteristics. For example, displaying suggestions like "Top favorite products in the tech lover's community", or "Suggestions from users with similar consumption habits to yours". This helps increase trust in product choices while supporting users in discovering products they have never thought of but that are very suitable.

5.2.4 Regarding trust

The factor "Trust" has the strongest influence on purchase intention, with a standardized regression coefficient of 0.357. To enhance trust, it is necessary to ensure that the proposed products are not only suitable but also of high quality. E-commerce platforms should integrate the feature of "hiding product suggestions" so that users can proactively eliminate irrelevant recommendations, thus feeling respected and in control of the displayed content. Data from the behavior of "hiding products" also serves as an indirect source of feedback, helping the AI system adjust its algorithms to make recommendations more accurate and relevant. In addition, blockchain technology is used to verify the origin and quality of products. Each product will be assigned a unique verification code, allowing consumers to trace all information related to the production, distribution, and certification processes of the product. Notifications such as “Product has been verified” will be prominently displayed on the product page, providing maximum reassurance to customers. The combination of AI and blockchain will create a transparent and reliable ecosystem, where AI is responsible for analyzing, learning consumer behavior, and providing personalized recommendations, while blockchain ensures the authenticity of the product and related data.

5.2.5 Regarding immersive experience

Research results indicate that the immersive experience is the second strongest factor influencing customers’ purchase intention on e-commerce platforms, with a standardized regression coefficient of 0.332. Optimizing page load speed and interface smoothness should be a top priority for e-commerce platforms, particularly when consumers are switching between products or categories. Users will be able to stay focused and spend more time interacting with product recommendations if the experience is smooth and uninterrupted. Additionally, by using AI to recall past actions and browsing history, an immersive experience must be developed as a habit of repeated attachment. To arouse users’ emotional recollections, the platform might offer recommendations like “continue exploring from last time” or “you liked this product.” Because of this, they return to a state of immersion in a matter of seconds after gaining access, which is essential in the current competitive environment. AI should be applied to recognize and adapt to users’ moods, thereby personalizing recommendations not only based on behavioral profiles but also on current emotions. By offering simple emotional choices (“How do you feel today?”), the system can automatically adjust the type of suggested products, for example, essential oils and books if the user wants to relax, or colorful fashion accessories if they are feeling happy, which will help upgrade the experience from “appropriate” to “empathetic”.

5.2.6 Regarding perceived usefulness

The research results indicate that perceived usefulness is the third most significant factor influencing users’ purchase intentions on e-commerce platforms, with a standardized regression coefficient of 0.292. To enhance users’ perception of usefulness, the application of AI in recommendation systems plays a key role. AI can collect and analyze user behavior data from various sources such as Shopee Live, Shopee Video, search queries, interaction time with products, etc., in order to provide increasingly precise personalized recommendations. The AI system can also automatically identify related products or those with similar consumption trends, helping users access more suitable choices without wasting time on manual searches. At the same time, it should integrate a smart comparison feature between equivalent products right within the suggestions, thanks to AI analyzing the prominent differences in price, features, and user reviews. These recommendations will help shorten the shopping journey. These applications not only enhance the perception of the system’s usefulness but also contribute to improving conversion rates and sustaining user retention.

6. Research Limitations and Future Research Directions

6.1 Research Limitations

Firstly, during the implementation process, the research team encountered some difficulties in accessing experts due to limited time for discussions and busy work schedules. In addition, since the research topic is still relatively new in Vietnam, domestic reference materials are limited, making it difficult to find theoretical foundations. Meanwhile, most of the reference materials are from foreign sources, which affects the accuracy and completeness of accessing specialized content.

Secondly, although 400 valid survey responses were collected, this number is still not large enough to represent the entire customer base using e-commerce platforms in Vietnam. Therefore, the research results are only for reference for a portion of consumers and cannot fully reflect the impact of AI-based personalization on user purchasing behavior on this platform.

Although the study has certain limitations, it still meets the set objectives and brings some new insights in terms of theoretical models as well as methodological approaches. In particular, in the context of Vietnam, there is still limited in-depth research on the impact of personalization on e-commerce platforms. This study contributes to opening up potential research directions for the future, while also providing practical foundations and proposing appropriate managerial implications to promote consumer purchase intentions on e-commerce platforms.

6.2 Future Research Directions

Firstly, future studies should use greater sample sizes to broaden the scope of surveys. This will more accurately depict how much AI-based personalization affects consumers’ intents to make purchases on e-commerce sites in the actual setting of different Vietnamese groups. Furthermore, conducting surveys over an extended period of time will aid in assessing shifts in consumer behavior.

Secondly, the sample size was nevertheless constrained even though the study integrated both quantitative and qualitative methodologies to obtain deeper insights into customer perceptions and experiences using AI-powered personalization features. To improve the validity and generalizability of the research findings, future studies could use a larger sample size for focus groups or in-depth interviews as well as more varied sampling techniques.

Thirdly, the effect of personalization on consumers' perceptions of privacy and acceptance of technology is a crucial research area that must be taken into account. Customers may get concerned about being overly monitored in the context of e-commerce platforms, which are gathering more and more personal data to improve the shopping experience. This could have a detrimental impact on their intents to make purchases. Future studies could therefore evaluate the degree of privacy concerns and the readiness to embrace new technologies like AI-powered customization.

Author Contributions

Conceptualization, validation, methodology, investigation, statistical analysis, and writing the original draft, P.N.K., L.T.N.D., and D.T.T.N.; analysis improvement, review and editing, supervision, P.N.K.; redesigning the experiments/collecting important additional data to strengthen the results, software, statistical analysis, contributed to discussing the conclusions, P.N.K., L.T.N.D., and D.T.T.N.; reviewing the literature and improving the linguistic style of the draft, P.N.K. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

Accenture. (2024). *The Empowered Consumer*. https://www.accenture.com/hk-en/insights/consulting/empowered-consumer

Accesstrade Vietnam. (2025). *Report on Affiliate Marketing*. https://accesstrade.vn

Advertising Vietnam. (2024). *Overview Report 2024 & Forecast 2025*. https://www.tranvanloi.name.vn/2025/02/bao-cao-tmdt-vn-nam-2024.html

Ajzen, I. (1980). Understanding attitudes and predicting social behavior. *Englewood Cliffs.*

Alhijawi, B., Awajan, A., & Fraihat, S. (2022). Survey on the objectives of recommender systems: Measures, solutions, evaluation methodology, and new perspectives. *ACM Comput. Surv.*, *55*(5), 1–38. https://doi.org/10.1145/3527449.

Arslan, K. (2020). Eğitimde yapay zekâ ve uygulamaları. *Batı Anadolu Eğitim Bilim. Derg.*, *11*(1), 71–88.

Bain & Company. (2023). *E-Conomy SEA report*. https://www.thinkwithgoogle.com/_qs/documents/18380/e_conomy_sea_2023_report.pdf

Ballı, A. (2024). Comparison of studies conducted in the field of neuromarketing and artificial intelligence using bibliometric method. *J. Mehmet Akif Ersoy Univ. Econ. Adm. Sci. Fac.*, *11*(3), 980–1010. https://doi.org/10.30798/makuiibf.1416687.

Bawack, R. E., Wamba, S. F., Carillo, K. D. A., & Akter, S. (2022). Artificial intelligence in e-commerce: A bibliometric study and literature review. *Electron. Mark.*, *32*(1), 297–338. https://doi.org/10.1007/s12525-022-00537-z.

Bhagat, R., Chauhan, V., & Bhagat, P. (2023). Investigating the impact of artificial intelligence on consumer's purchase intention in e-retailing. *Foresight*, *25*(2), 249–263. https://doi.org/10.1108/fs-10-2021-0218.

Bloomenthal, A. (2021). *E-commerce Defined: Types, History, and Examples*. Investopedia. https://www.investopedia.com/terms/e/ecommerce.asp

Büyükdağ, N. (2021). The effect of brand awareness, brand image, satisfaction, brand loyalty and WOM on purchase intention: An empirical research on social media. *Bus. Manag. Stud. Int. J.*, *9*(4), 1380–1398. https://doi.org/10.15295/bmij.v9i4.1902.

Castells, P., Hurley, N., & Vargas, S. (2021). Novelty and diversity in recommender systems. In *Recommender Systems Handbook* (pp. 603–646). Springer US. https://doi.org/10.1007/978-1-0716-2197-4_16.

Chi, N. T. K. & Anh, B. N. T. (2024). Online shopping intent powered by artificial intelligence: The role of usefulness and personalization. *J. Finance Mark. Res.*, *15*(4), 79–93.

Chiu, H. C., Hsieh, Y. C., & Kao, C. Y. (2005). Website quality and customer's behavioural intention: An exploratory study of the role of information asymmetry. *Total Qual. Manag. Bus. Excell.*, *16*(2), 185–197.

https://doi.org/10.1080/14783360500054277.
Cremonesi, P., Garzotto, F., & Turrin, R. (2012). Investigating the persuasion potential of recommender systems from a quality perspective: An empirical study. *ACM Trans. Interact. Intell. Syst.*, *2*(2), 1–41. https://doi.org/10.1145/2209310.2209314.
Dangi, H. & Malik, A. (2017). Personalisation in marketing: An exploratory study. *Int. J. Internet Mark. Advert.*, *11*(2), 124–136. https://doi.org/10.1504/ijima.2017.084079.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.*, *13*(3), 319–340. https://doi.org/10.2307/249008.
El Alam, R. & Bitar, M. O. (2024). Unveiling the influence of AI's product recommendation on consumer purchase intent: A quantitative study investigating the role of AI product recommendations on consumer purchase intent [Diplomathesis, Mälardalen University]. https://urn.kb.se/resolve?urn=urn:nbn:se:mdh:diva-67008
Faqih, K. M. & Jaradat, M. I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *J. Retail. Consum. Serv.*, *22*, 37–52. https://doi.org/10.1016/j.jretconser.2014.09.006.
Fink, A. & Litwin, M. S. (1995). *How to Measure Survey Reliability and Validity (Vol. 7)*. Sage.
Fong, L. H. N. & Law, R. (2014). Hair, JF Jr., Hult, GTM, Ringle, CM, Sarstedt, M.(2014). A primer on partial least squares structural equation modeling (PLS-SEM). *Eur. J. Tour. Res.*, *6*(2), 211–213.
Gao, J., Zhang, C., Wang, K., & Ba, S. (2012). Understanding online purchase decision making: The effects of unconscious thought, information quality, and information quantity. *Decis. Support Syst.*, *53*(4), 772–781. https://doi.org/10.1016/j.dss.2012.05.011.
Gao, Y. & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective. *J. Res. Interact. Mark.*, *17*(5), 663–680. https://doi.org/10.1108/jrim-01-2022-0023.
García, A. S. & Margallo, E. M. (2014). Bullying: What's going on? A bibliographic review of last twelve months. *Procedia Soc. Behav. Sci.*, *132*, 269–276. https://doi.org/10.1016/j.sbspro.2014.04.309.
Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *Int. J. Multivar. Data Anal.*, *1*(2), 107–123. https://doi.org/10.1504/ijmda.2017.087624.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.
Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Trans. Inf. Syst.*, *22*(1), 5–53. https://doi.org/10.1145/963770.963772.
Hoffman, D. L. & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. *J. Mark.*, *60*(3), 50–68. https://doi.org/10.1177/002224299606000304.
Imhoff, S., Silva, A., Dias Junior, M. D. S., & Tormena, C. A. (2001). Quantifying critical pressures for plant growth. *Rev. Bras. Ciênc. Solo.*, *25*, 11–18. https://doi.org/10.1590/s0100-06832001000100002.
Jacoby, J. (2002). Stimulus-organism-response reconsidered: An evolutionary step in modeling (consumer) behavior. *J. Consum. Psychol.*, *12*(1), 51–57. https://doi.org/10.1207/s15327663jcp1201_05.
Jalilvand, M. R. & Samiei, N. (2012). The effect of electronic word of mouth on brand image and purchase intention. *Mark. Intell. Plann.*, *30*(4), 460–476. https://doi.org/10.1108/02634501211231946.
Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decis. Support Syst.*, *44*(2), 544–564. https://doi.org/10.1016/j.dss.2007.07.001.
Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems. *User Model. User-Adapt. Interact.*, *22*(4), 441–504. https://doi.org/10.1007/s11257-011-9118-4.
Li, M., Wang, Q., & Cao, Y. (2022). Understanding consumer online impulse buying in live streaming e-commerce: A stimulus-organism-response framework. *Int. J. Environ. Res. Public Health*, *19*(7), 4378. https://doi.org/10.3390/ijerph19074378.
Liao, J., Chen, K., Qi, J., Li, J., & Yu, I. Y. (2023). Creating immersive and parasocial live shopping experience for viewers: The role of streamers' interactional communication style. *J. Res. Interact. Mark.*, *17*(1), 140–155. https://doi.org/10.1108/jrim-04-2021-0114.
Lin, L. Y. (2011). The impact of advertising appeals and advertising spokespersons on advertising attitudes and purchase intentions. *Afr. J. Bus. Manage.*, *5*(21), 8446–8457. https://doi.org/10.5897/ajbm11.925.
Lu, Y. & Kim, J. (2023). The effect of the personalized recommendation system of online shopping platform on consumers' purchase intention. *Inf. Syst. Rev.*, *25*(4), 67–87.
Luo, C., Luo, X. R., Schatzberg, L., & Sia, C. L. (2013). Impact of informational factors on online recommendation credibility: The moderating role of source credibility. *Decis. Support Syst.*, *56*, 92–102. https://doi.org/10.1016/j.dss.2013.05.005.
MarketingAI. (2024). *Consumer Trends Report*. https://marketingai.vn/consumer-trends-report-66-khach-hang-

khong-chia-se-y-kien-ca-nhan-khi-gap-phai-trai-nghiem-khong-tot-194240220170723059.htm
McKinsey & Company. (2024). *State of the Consumer 2025: When Disruption Becomes Permanent*. https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/state-of-consumer
Mehrabian, A. & Russell, J. A. (1974). *An Approach to Environmental Psychology*. The MIT Press.
Montgomery, A. L. & Smith, M. D. (2009). Prospects for personalization on the Internet. *J. Interact. Mark.*, *23*(2), 130–137. https://doi.org/10.1016/j.intmar.2009.02.001.
Mukherjee, A. & Nath, P. (2007). Role of electronic trust in online retailing: A re-examination of the commitment-trust theory. *Eur. J. Mark.*, *41*(9/10), 1173–1202. https://doi.org/10.1108/03090560710773390.
Panniello, U., Gorgoglione, M., & Tuzhilin, A. (2016). Research note—In CARSs we trust: How context-aware recommendations affect customers' trust and other business performance measures of recommender systems. *Inf. Syst. Res.*, *27*(1), 182–196. https://doi.org/10.1287/isre.2015.0610.
Park, S. H. & Han, S. P. (2013). From accuracy to diversity in product recommendations: Relationship between diversity and customer retention. *Int. J. Electron. Commer.*, *18*(2), 51–72. https://doi.org/10.2753/jec1086-4415180202.
Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). AI and its implications for market knowledge in B2B marketing. *J. Bus. Ind. Mark.*, *34*(7), 1410–1419. https://doi.org/10.1108/jbim-10-2018-0295.
Pognonec, J. & Bornard, T. (2023). *The effect of artificial intelligence and product recommendation on purchase intention: A study of the cosmetics field* [Mastersthesis]. Handelshoyskolen BI.
Pu, P., Chen, L., & Hu, R. (2011). A user-centric evaluation framework for recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems* (pp. 157–164). https://doi.org/10.1145/2043932.2043962.
Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. *Int. J. Res. Mark.*, *36*(3), 350–366. https://doi.org/10.1016/j.ijresmar.2018.12.002.
Rondán-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. *Kybernetes*, *44*(5), 788–805. https://doi.org/10.1108/k-09-2014-0184.
Roudposhti, V. M., Nilashi, M., Mardani, A., Streimikiene, D., Samad, S., & Ibrahim, O. (2018). A new model for customer purchase intention in e-commerce recommendation agents. *J. Int. Stud.*, *11*(4), 237–253.
Senthilnathan, S. & Tharmi, U. (2012). The relationship of brand equity to purchase intention. *ICFAI J. Mark. Manag.*, *11*(2), 7.
Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Meunier-FitzHugh, K. L., Malshe, A., Mullins, R., & Onyemah, V. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: Concepts, priorities, and questions. *J. Pers. Sell. Sales Manag.*, *39*(1), 2–22. https://doi.org/10.1080/08853134.2018.1557525.
Statista. (2025). *Statista Market Insights*. https://www.statista.com/outlook/
Tabachnick, B. G. & Ullman, J. B. (2007). *Using Multivariate Statistics (Vol. 5)*. Pearson.
Tavera, J. F. & Londoño, B. E. (2014). Factores determinantes de la aceptación tecnológica del e-commerce en países emergentes. *Rev. Cienc. Estrateg.*, *22*(31), 101–119.
Tran, L. T. T. (2021). Managing the effectiveness of e-commerce platforms in a pandemic. *J. Retail. Consum. Serv.*, *58*, 102287. https://doi.org/10.1016/j.jretconser.2020.102287.
Trong, H. & Ngoc, C. N. M. (2008). *Research Data Analysis with SPSS.* Hong Duc Publisher, Ho Chi Minh City. https://sachvui.com/ebook/phan-tich-du-lieu-nghien-cuu-voi-spss-tap-1-hoang-trong-chu-nguyen-mong-ngoc.857.html
Vesanen, J. (2007). What is personalization? A conceptual framework. *Eur. J. Mark.*, *41*(5/6), 409–418. https://doi.org/10.1108/03090560710737534.
Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of Partial Least Squares*. Springer Berlin Heidelberg. http://dx.doi.org/10.1007/978-3-540-32827-8.
Yang, X. (2020). Influence of informational factors on purchase intention in social recommender systems. *Online Inf. Rev.*, *44*(2), 417–431. https://doi.org/10.1108/oir-12-2016-0360.
Yang, X. (2021). Determinants of consumers' continuance intention to use social recommender systems: A self-regulation perspective. *Technol. Soc.*, *64*, 101464. https://doi.org/10.1016/j.techsoc.2020.101464.
Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI-personalized recommendations on clicking intentions: Evidence from Chinese e-commerce. *J. Theor. Appl. Electron. Commer. Res.*, *20*(1), 21. https://doi.org/10.3390/jtaer20010021.
Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *Int. J. Hum. Comput. Stud.*, *131*, 160–178. https://doi.org/10.1016/j.ijhcs.2019.06.006.
Zhang, Z. & Tao, D. (2012). Slow feature analysis for human action recognition. *IEEE Trans. Pattern Anal. Mach. Intell.*, *34*(3), 436–450. https://doi.org/10.1109/tpami.2011.157.
Zhao, J. & Wang, J. (2020). Health advertising on short-video social media: A study on user attitudes based on the extended technology acceptance model. *Int. J. Environ. Res. Public Health.*, *17*(5), 1501.

https://doi.org/10.3390/ijerph17051501.
Zhao, L., Fu, B., & Bai, S. (2025). Understanding the influence of personalized recommendation on purchase intentions from a self-determination perspective: Contingent upon product categories. *J. Theor. Appl. Electron. Commer. Res.*, *20*(1), 32. https://doi.org/10.3390/jtaer20010032.

Appendix

Table A1. Load factor test results

Variables	CLHT	CLTT	LT	SDM	SHI	TNDC	YD
CLHT1	0.750						
CLHT2	0.772						
CLHT3	0.799						
CLHT4	0.728						
CLHT5	0.798						
CLHT6	0.802						
CLTT1		0.757					
CLTT2		0.795					
CLTT3		0.773					
CLTT4		0.756					
CLTT5		0.758					
CLTT6		0.754					
LT1			0.846				
LT2			0.808				
LT3			0.821				
SDM1				0.761			
SDM2				0.805			
SDM3				0.731			
SDM4				0.793			
SDM5				0.764			
SHI1					0.811		
SHI2					0.816		
SHI3					0.723		
SHI4					0.824		
TNDC1						0.795	
TNDC2						0.785	
TNDC3						0.839	
TNDC4						0.794	
YD1							0.795
YD2							0.831
YD3							0.854

Table A2. Results of in-depth interviews in preliminary qualitative research

Factor Statistics				**Observed Variable**	
Factor	Encode	Agree (1)	Disagree (2)	Observation variable belonging to the pre-adjustment scale	Observation variable belonging to the adjusted scale
Innovation	SDM1	10/10		E-commerce platforms can offer personalized recommendations for some unique products that customers have never known before.	No change
	SDM2			Products recommended by e-commerce platforms through personalized suggestions provide a fresh feeling.	No change
	SDM3			Personalized recommendations from e-commerce platforms help discover newly launched products on the market.	No change
	SDM4			E-commerce platforms can offer personalized suggestions for certain unique products.	No change
	SDM5			E-commerce platforms can offer personalized suggestions for certain products that are more creative than previous ones.	No change

Information quality	CLTT1	10/10		E-commerce platforms will suggest personalized products that customers are interested in.	No change
	CLTT2			E-commerce platforms will suggest personalized products that match individual preferences.	No change
	CLTT3			E-commerce platforms will recommend personalized products that customers need.	No change
	CLTT4			The personalized product recommendation content on e-commerce platforms is presented in detail.	No change
	CLTT5			Personalized product recommendations on e-commerce platforms will provide all the necessary topics.	No change
	CLTT6			Personalized product recommendations on e-commerce platforms will provide complete product information.	No change
System quality	CLHT1	10/10		E-commerce platforms recommend a variety of personalized products.	No change
	CLHT2			E-commerce platforms offer personalized recommendations across various categories.	No change
	CLHT3			E-commerce platforms recommend personalized products from various brands.	No change
	CLHT4			E-commerce platforms recommend personalized products at various price points.	No change
	CLHT5			E-commerce platforms will accurately suggest the products customers need when they enter search keywords.	E-commerce platforms will accurately personalize product recommendations for customers based on the search keywords they enter.
	CLHT6			E-commerce platforms will accurately recommend the products customers need when searching by image.	E-commerce platforms will accurately personalize product recommendations for customers when searching by image.
Immersion experience	TNDC1	9/10	1/10	The personalized recommendations of e-commerce platforms immerse customers in a continuous stream of product suggestions.	No change
	TNDC2			Personalized product recommendations from e-commerce platforms that attract customers must always encourage interaction on the site.	No change
	TNDC3			The personalized product recommendations from e-commerce platforms make customers feel like they are only shopping for a short period, but in reality, they have been shopping for a long time.	No change
	TNDC4			The continuous personalized product recommendations from e-commerce platforms make customers get immersed and forget their original purpose for shopping.	No change
Perceived usefulness	SHI1	10/10		Personalized product recommendations on e-commerce platforms make it easier to find products with the best quality.	No change
	SHI2			Personalized product recommendations on e-commerce platforms help find products faster.	No change
	SHI3			Personalized product recommendations	No change

			on e-commerce platforms help find products that match users' needs.	
	SHI4		Personalized product recommendations on e-commerce platforms make shopping more convenient compared to when there are no such suggestions.	No change
Trust	LT1	10/10	E-commerce platforms always recommend high-quality products.	E-commerce platforms always recommend personalized high-quality products.
	LT2		E-commerce platforms always suggest personalized products that match users' preferences.	No change
	LT3		Product recommendations on e-commerce platforms are always accurate.	Personalized product recommendations on e-commerce platforms are always accurate.
Purchase intention	YD1	10/10	I am thinking about buying products through the personalized recommendations of e-commerce platforms.	No change
	YD2		I am willing to purchase products through personalized recommendations from e-commerce platforms.	No change
	YD3		I will buy products through the personalized recommendations of e-commerce platforms.	No change