# “AI and online purchase decisions: The mediating role of attitude”

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| **ARTICLE INFO** | Le Thi Kim Hoa (2025). AI and online purchase decisions: The mediating role of attitude. *Innovative Marketing* , *21*(4), 305-317. doi:10.21511/im.21(4).2025.22 |
| **DOI** | http://dx.doi.org/10.21511/im.21(4).2025.22 |
| **RELEASED ON** | Friday, 19 December 2025 |
| **RECEIVED ON** | Monday, 18 August 2025 |
| **ACCEPTED ON** | Tuesday, 02 December 2025 |

| | |
|---|---|
| **JOURNAL** | "Innovative Marketing " |
| **ISSN PRINT** | 1814-2427 |
| **ISSN ONLINE** | 1816-6326 |
| **PUBLISHER** | LLC “Consulting Publishing Company “Business Perspectives” |
| **FOUNDER** | LLC “Consulting Publishing Company “Business Perspectives” |

| NUMBER OF REFERENCES | NUMBER OF FIGURES | NUMBER OF TABLES |
|---|---|---|
| **38** | **3** | **8** |



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# AI AND ONLINE PURCHASE DECISIONS: THE MEDIATING ROLE OF ATTITUDE

## Abstract

By altering how people evaluate information, utilize technology, and make purchasing decisions, Artificial Intelligence (AI) is transforming the way customers shop online. This study aims to examine the mediating role of attitudes toward AI in the relationship between cognitive and psychological factors and online purchase decisions. A mixed-methods design with two phases was used. To improve and culturally validate the measurement items, five marketing and e-commerce specialists were interviewed in May 2025 as part of the qualitative phase of the study. During the quantitative phase, customers in Ho Chi Minh City who regularly shop on major e-commerce platforms were invited to complete a structured online survey between June 1 and July 15, 2025. A self-administered online questionnaire disseminated via Facebook and Zalo yielded 458 valid responses. Respondents were selected because they frequently interact with AI-enabled features, such as recommendation systems, chatbots, and personalized interfaces, making them highly relevant to the study's objectives. SmartPLS 4.0 and SPSS 26.0 were used to analyze the data. Cronbach's Alpha, EFA, CFA, and PLS-SEM were used to confirm reliability, convergent validity, and discriminant validity. The results indicate that Attitude toward AI are significantly influenced by Perceived Usefulness (PU), Ease of Use, Trust, and Enjoyment. The desire to make an online purchase is strongly positively impacted by attitude ($\beta = 0.327$; $p < 0.001$; $R^2 = 0.135$). These findings emphasize the importance of enhancing trust, usability, and emotional value in AI-driven e-commerce settings by highlighting the crucial role that customer attitudes play in shaping AI-related perceptions into buying intentions.

**Keywords** Artificial Intelligence, attitude, trust, subjective norm, perceived usefulness, purchase intention, e-commerce

**JEL Classification** M31, M15, O33

**Type of the article:** Research Article

**Received on:** 18th of August, 2025
**Accepted on:** 2nd of December, 2025
**Published on:** 19th of December, 2025



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

## INTRODUCTION

The widespread integration of Artificial Intelligence (AI) into digital commerce platforms has significantly redefined consumer behavior. As AI technologies, such as recommendation engines, personalization algorithms, and autonomous decision-making systems, become increasingly prevalent in online shopping, traditional approaches to evaluating customer preferences are being redefined (Kaplan & Haenlein, 2019; Dai & Liu, 2024). Consumers now interact with AI not only as passive users but also as co-decision-makers in highly automated environments (Dwivedi et al., 2021).

Despite the growing sophistication of AI systems, existing theoretical frameworks struggle to explain how consumers form attitudes toward these technologies and how such attitudes influence purchase decisions. Insights from cognitive psychology, behavioral science, and information systems research remain fragmented and have yet to converge into a comprehensive model that demonstrates how evaluative beliefs, emotional experiences, and normative expectations interact (Ajzen, 1991; Davis, 1989; Venkatesh & Davis, 2000; Tussyadiah, 2020).

In particular, the mediating role of attitude – a crucial psychological mechanism – remains underdeveloped in the context of AI-assisted decision-making. While many studies have examined attitudes as direct predictors of behavioral intention, few have explored how attitudes connect cognitive appraisals with actual behaviors in algorithmically mediated shopping environments (Dwivedi et al., 2021; Chen et al., 2023). This gap is especially important because understanding the mediating function of attitude helps clarify how cognitive, emotional, and social factors jointly shape consumers' acceptance of AI technologies.

This study fills in those gaps by proposing and testing an integrated model that examines how cognitive, affective, and social-normative factors influence consumers' perceptions of AI-enabled systems and how these attitudes, in turn, affect online purchase intentions. The model is tested with Generation Z consumers in Vietnam, an emerging market characterized by significant digital activity and ongoing concerns regarding data privacy, algorithmic transparency, and trust in AI systems (Nguyen, 2024; Nguyen et al., 2024a; Rafi, 2023).

# 1. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

## 1.1. Theoretical background

With the rapid advancement of Artificial Intelligence (AI) in digital business ecosystems, the cognitive and behavioral processes underlying consumer decision-making have undergone significant transformation. AI-powered systems are no longer passive tools; instead, they increasingly function as co-decision-makers that analyze customer data, predict customer preferences, and make highly personalized suggestions in real time (Kaplan & Haenlein, 2019; Dai & Liu, 2024). These systems employ techniques such as predictive behavior analysis, adaptive filtering, and personalized matching to influence consumer choices across platforms (OECD, 2019; Dwivedi et al., 2021).

Contemporary consumers engage with AI systems through predictive analytics, recommendation engines, and contextual search tools. These tools alter how people obtain information, make decisions, and evaluate their options (Frita et al., 2024; Grewal et al., 2017; Kotler & Keller, 2022; Laudon & Traver, 2021). As AI continues to expand its functional scope, a need has emerged to understand how users cognitively and emotionally interpret algorithmic decision-support tools, particularly when these tools supplement or replace human judgment (Ajzen, 1991; Kaplan & Haenlein, 2019).

Several theories attempt to explain how people interact with and communicate through AI systems. Technology Acceptance Model (TAM) suggests that consumers' perceptions of new technologies are primarily based on their perceived usefulness and ease of use (Davis, 1989; Venkatesh & Davis, 2000; Elia et al., 2021). In digital settings, these cognitive evaluations are critical when there is excessive information or complexity. AI can make it easier to compare products and make decisions. However, cognitive assessments alone are insufficient to fully explain how people accept new technologies. When people evaluate AI-powered systems, emotions such as enjoyment, satisfaction, and affective engagement are crucial (Chen et al., 2023; Tussyadiah, 2020; Van der Heijden, 2004). Simultaneously, social influences – normative expectations, peer validation, and cultural signals – affect how consumers assess AI recommendations, particularly in ambiguous or high-risk scenarios (Ajzen, 1991; Fishbein & Ajzen, 1975).

Despite the wealth of empirical evidence supporting these dimensions, much of the literature tends to examine them in isolation. Behavioral intention studies emphasize attitudes, normative beliefs, and perceived control, while TAM-based studies focus on task-related efficiency (Davis, 1989; Venkatesh & Davis, 2000). Studies on trust underscore the importance of system transparency, predictability, and reliability – especially in e-commerce contexts where privacy and financial risks are heightened (Gefen et al., 2003; Khairy et al., 2025; Pavlou & Gefen, 2004). Digital experience research further indicates that gamification, per-


http://dx.doi.org/10.21511/im.21(4).2025.22

sonalization, and engagement have a significant influence on satisfaction with AI-driven shopping processes (Dai & Liu, 2024; Nagy & Hajdu, 2021).

There is a serious theoretical problem with this disparity in study perspectives. According to Russell and Norvig (2021) and Dwivedi et al. (2021), studies on social norms often overlook issues related to system usability, whereas studies on cognition tend to disregard emotional variables. According to Afri et al. (2021) and Dai and Liu (2024), customers' satisfaction with a product may not necessarily match their motivations for purchasing it or their opinion of the brand's reliability. This discrepancy highlights a larger issue: there is no well-defined theory that considers the social, emotional, and mental aspects of human-AI interaction. In this sense, attitude is a potential but immature construct. Although attitudes have historically been treated as a linear predictor of behavioral intention (Ajzen, 1991), they can also act as mediators, connecting behavioral responses and cognitive assessments (such as perceived usefulness). This mediating function is still not well understood in scenarios involving AI-specific decision-making, though.

Finally yet importantly, culture plays a significant role in how people respond to AI. People's judgment of the effects of AI depends on their level of technical knowledge, risk tolerance, and cultural awareness, among other factors. People in developing nations, such as Vietnam, where e-commerce is growing rapidly, still have significant concerns about trust, data security, and algorithmic transparency (Nguyen, 2024; Nguyen et al., 2024a). Emotions and social norms play a significant role in shaping consumer attitudes in such contexts, as interpersonal trust and social approval are particularly valued in such cultural settings.

## 1.2. Research gaps and rationale

Existing studies provide us with a wealth of helpful information about how personal factors influence people's decisions to use technology and their online habits; however, they still have three major flaws that need to be addressed. First, empirical studies predominantly rely on isolated theoretical lenses – either focusing on cognitive beliefs derived from technology-acceptance models or examining social influence and behavioral intention through psychological theories. We do not fully understand how these different aspects work together in AI-driven environments, where automated decision-support systems simultaneously cause cognitive processing, social norms, and emotional reactions (Ajzen, 1991; Dai & Liu, 2024; Davis, 1989; PwC, 2020). As a result, there is no unified explanatory framework that captures the combined pathways through which these elements shape overall consumer attitudes toward AI.

Second, prior research often treats attitudes as a direct predictor of intention, without analyzing how attitudes function as a mediating mechanism. However, a new study shows that the attitude layer is essential for combining the effects of outside factors like trust, perceived usefulness, perceived enjoyment, and subjective norms into behavior that makes sense (Arfi et al., 2021; Frita et al., 2024; Nagy & Hajdu, 2021). Yet evidence from related streams – such as continuance intention in mobile commerce and post-adoption satisfaction/retention – suggests additional attitudinal pathways that are rarely integrated into AI-shopping contexts (Evelina, 2022; Gao et al., 2015). No one knows for sure why some customers accept suggestions made by AI. In contrast, others do not, even though both groups are exposed to similar technological features, because there is not a complete mediation structure.

Contextual differences also remain insufficiently explained. Studies on technology-enabled service settings indicate that relationship constructs (e.g., satisfaction → trust → loyalty) can condition downstream behavior, but these mechanisms are seldom examined for AI-mediated shopping (Wilson et al., 2021). Moreover, research on AI touchpoints like service chatbots and AI-driven engagement points to novel acceptance determinants that current models underutilize (Auer et al., 2024; Hensman et al., 2024). Vietnamese shoppers are increasingly turning to online shopping, but not all of them trust the internet. This means that people are using AI for reasons other than its utility. Furthermore, they are concerned about the perceived safety of automatic systems (Khairy et al., 2025; Nguyen, 2024; Nguyen et al., 2023). Very few studies integrate psychosocial variables, cognitive appraisals, and emotional outcomes in this context, leaving a gap in understanding the mechanisms that shape AI-enabled purchase intention in emerging markets.

Due to these issues with theory and practice, it is crucial to integrate the predictive power of cognitive views (PU, PEOU), psychosocial effects (subjective norm, trust), and experiential responses (perceived enjoyment) into a structured mediation framework. Filling in this gap will help researchers understand how these ideas interact to shape consumers' perceptions of AI and, in turn, their online purchasing plans. Accordingly, we develop and test a unified mediation framework in which attitude toward AI integrates trust, subjective norms, and cognitive and experiential appraisals to explain purchase intention in AI-enabled online shopping. This study addresses this need by proposing and testing an integrated model that explains how customers interact in AI-powered online stores.

## 1.3. Research hypotheses and conceptual model

People judge AI-powered e-commerce systems based on their trust, subjective standards, cognitive beliefs, and personal experiences. People who trust digital platforms expect them to work honestly and effectively, which lowers uncertainty and leads to positive opinions of technology (Akbar et al., 2024; Gefen et al., 2003; Pavlou & Gefen, 2004; Wilson et al., 2021). It has already been found that when people trust a platform, they perceive AI-powered features as better and easier to use. This makes their positive cognitive assessments stronger (Auer et al., 2024; Nagy & Hajdu, 2021; Nguyen et al., 2024b). Subjective norms, or social pressure from people whose opinions are considered necessary, also influence how people accept and perceive the usefulness of technology. Prior work shows that normative impact strengthens perceived usefulness and acceptance in AI-supported shopping environments (Ajzen, 1991; Ruslan & Aziz, 2024; Sharma et al., 2016; Venkatesh & Davis, 2000).

The primary factors that influence consumers' perceptions of technology are their cognitive views, particularly their Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). People tend to feel more positive about AI when they believe that tasks utilizing AI are helpful, easy to use, or enhance performance (Davis, 1989; Laudon & Traver, 2021). Studies show that PU and PEOU play a significant role in how people perceive AI in digital commerce (Dai & Liu, 2024; Evelina, 2022; Gao et al., 2015; Nagy & Hajdu, 2021). Perceived Enjoyment (PE) also measures the natural happiness people get from interacting with AI systems. Having fun with AI-enabled services makes people more likely to have a positive attitude and use them (Davis, 1989; Davis et al., 1992; Tussyadiah, 2020; Van der Heijden, 2004). The way people feel about Artificial Intelligence (AI) is a key factor that connects their thoughts and feelings with their decision to buy something (Dai & Liu, 2024; Kotler & Keller, 2022; Nagy & Hajdu, 2021).

Accordingly, based on the above theoretical framework, this study proposes the following research hypotheses:

H1: *Trust (T) has a positive effect on Perceived Usefulness.*

H2: *Trust (T) has a positive effect on Perceived Ease of Use.*

H3: *Subjective Norm (SN) has a positive effect on Perceived Usefulness.*

H4: *Subjective Norm (SN) has a positive effect on Perceived Ease of Use.*

H5: *Perceived Usefulness (PU) has a positive effect on Attitude toward AI.*

H6: *Perceived Ease of Use (PEOU) has a positive effect on Attitude toward AI.*

H7: *Perceived Enjoyment (PE) has a positive effect on Attitude toward AI.*

H8: *Attitude toward AI (AAI) has a positive effect on online Purchase Intention.*

H9: *Trust positively influences Attitude toward AI through the mediating role of Perceived Usefulness.*

H10: *Trust positively influences Attitude toward AI through the mediating role of Perceived Ease of Use.*



http://dx.doi.org/10.21511/im.21(4).2025.22

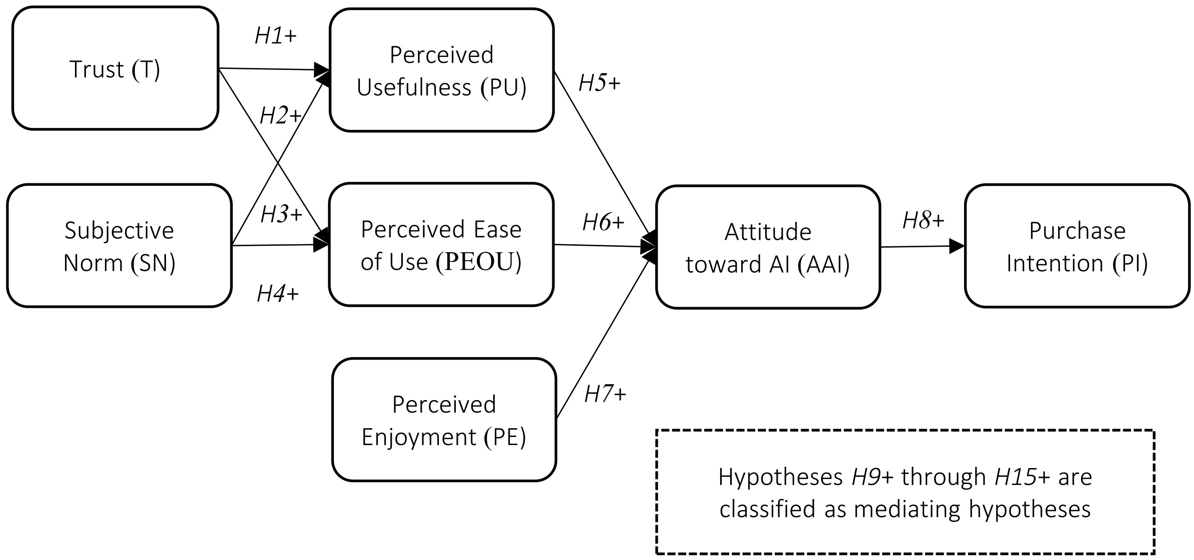


**Figure 1.** Proposed research model

*H11: Subjective Norm positively influences Attitude toward AI through the mediating role of Perceived Usefulness.*

*H12: Subjective Norm positively influences Attitude toward AI through the mediating role of Perceived Ease of Use.*

*H13: Perceived Usefulness positively influences online Purchase Intention through the mediating role of Attitude toward AI.*

*H14: Perceived Ease of Use positively influences online Purchase Intention through the mediating role of Attitude toward AI.*

*H15: Perceived Enjoyment positively influences online Purchase Intention through the mediating role of Attitude toward AI.*

Figure 1 illustrates the proposed conceptual model and the relationships among the variables.

## 2. METHODOLOGY

This study used a two-phase mixed-methods design conducted in Ho Chi Minh City, Vietnam, between May and July 2025 – a period and location chosen for the high penetration of AI-enabled e-commerce. First, a qualitative refinement was carried out in May 2025 with five purposively selected experts (two university lecturers in digital marketing and three senior managers from major platforms). Participants received study information, assurances of confidentiality, and withdrawal rights; all provided informed consent. Expert feedback was used to assess clarity, cultural suitability and redundancy of items; wording was then revised accordingly.

Next, an online survey (June 1 – July 15, 2025) targeted residents ≥ 18 years or older who had recently purchased from Shopee, Lazada, Tiki or TikTok Shop, accessed via Facebook and Zalo groups. We collected 487 responses and retained 458 valid cases after verifying completeness/consistency and eliminating duplicate IP addresses. No personally identifying data were recorded; participation was voluntary and anonymous. The instrument adapted validated scales for Trust, Subjective Norm, Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, Attitude toward AI, and Purchase Intention from prior literature; wording was aligned with recent evidence on AI-enabled purchase intention in Vietnam (Nguyen et al., 2024b). The complete questionnaire appears in the Appendix (a repository link can be provided) (Hair et al., 2019).

The data were processed in two steps: SPSS 26.0 was used for descriptive statistics, Cronbach's Alpha, and exploratory factor analysis; SmartPLS 4.0 was used for confirmatory factor analysis, testing of convergent/discriminant validity, and PLS-SEM hypothesis testing. Reporting and evaluation were conducted in accordance with current best practices. The study adhered to the institution's ethical standards; formal committee approval was not required for this type of low-risk survey research. The results of the analysis form the basis for the next part.

The outcomes of this methodological process provide the empirical foundation for the results and discussions reported in the following section.

The final sample consisted of 458 valid responses from individuals in Ho Chi Minh City who were at least 18 years old. Approximately 52.62 percent of them were women, and most were between the ages of 20 and 35 or 35 and 45. Most respondents held college or university degrees (81.44%), and the majority worked in offices (60.70%). In terms of income, 53.93% of respondents reported earning between VND 10 and 20 million per month. Most of the people who answered said they shopped online between one and three times a month, mainly on Shopee and Lazada. Based on these factors, the group is predominantly composed of young to middle-aged, educated, and digitally active individuals in Vietnam's cities.

The detailed demographic breakdown is shown in Table 1. This provides a foundation for examining the structural relationships among variables in the next section.

Overall, the descriptive statistics provide a clear picture of the sample characteristics, serving as a foundation for analyzing the factors influencing online purchase intentions in the subsequent sections of the study.

# 3. RESULTS

This study first reports the measurement model (reliability, convergent/discriminant validity), followed by the structural model and hypothesis testing. Paths were assessed via PLS-SEM with bootstrap (5,000 resamples; two-tailed). Discriminant validity was evaluated using HTMT, and collinearity using VIF.

Following the removal of the observed variable AAI1 since its outer loading was less than the suggested cutoff of 0.7 (0.660), SmartPLS 4.0 was used to reanalyze the structural model. The findings

**Table 1.** Descriptive statistics results (N = 458)

| Category | Characteristics | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 217 | 47.38 |
| | Female | 241 | 52.62 |
| Age | 18-19 | 73 | 15.94 |
| | 20-34 | 202 | 44.10 |
| | 35-45 | 178 | 38.86 |
| | 45+ | 5 | 1.09 |
| Education level | High school | 22 | 4.80 |
| | College/university | 373 | 81.44 |
| | Postgraduate | 63 | 13.76 |
| Occupation | Student | 25 | 5.46 |
| | Office employee | 278 | 60.70 |
| | Self-employed/business | 132 | 28.82 |
| | Others | 23 | 5.02 |
| Monthly income | Below VND 5 million | 30 | 6.55 |
| | VND 5-under 10 million | 130 | 28.38 |
| | VND 10-under 20 million | 247 | 53.93 |
| | Above VND 20 million | 51 | 11.14 |
| Most frequently used e-commerce platform | Lazada | 128 | 27.95 |
| | Shopee | 155 | 33.84 |
| | TikTok Shop | 74 | 16.16 |
| | Tiki | 101 | 22.05 |
| Frequency of online shopping | Less than once/month | 125 | 27.29 |
| | 1-3 times/month | 207 | 45.20 |
| | More than 3 times/month | 126 | 27.51 |
| Total | | 458 | 100.00 |


http://dx.doi.org/10.21511/im.21(4).2025.22

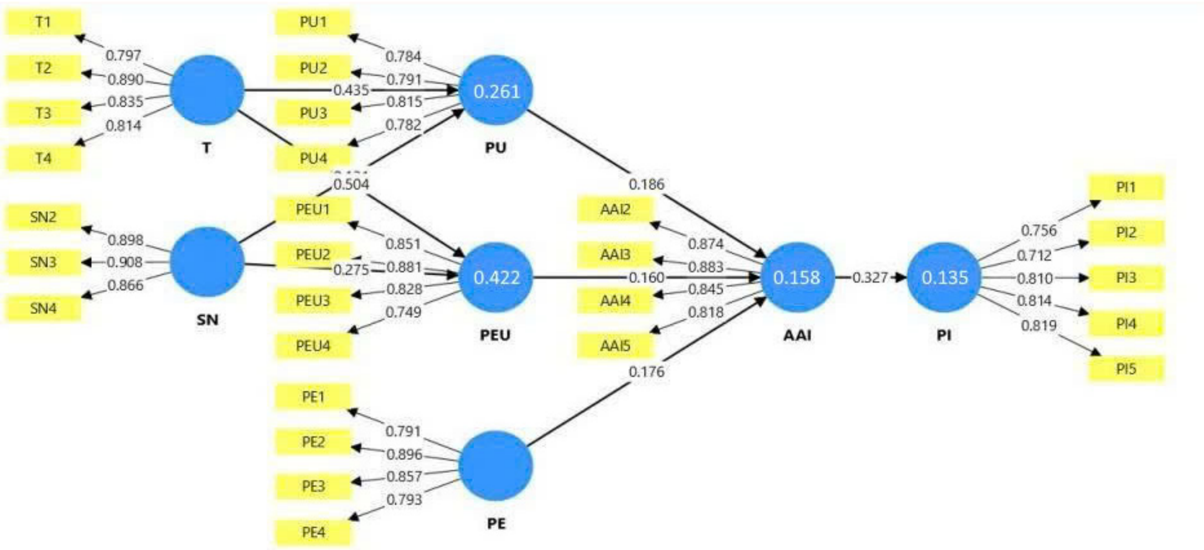


**Figure 2.** Measurement and structural links after removing AAI1 (SmartPLS 4.0)

are displayed in Figure 2, which shows the correlations between the latent variables, the model's dependent variables' coefficient of determination ($R^2$), and the standardized path coefficients (β).

According to Figure 2, PU and PEOU are positively affected by Trust (T) and Subjective Norm (SN). The strongest paths are T → PEOU (β = 0.504) and SN → PU (β = 0.504), followed by T → PU (β = 0.435); SN → PEOU (β = 0.275) is weaker. AAI is positively predicted by PU (β = 0.186), PEOU (β = 0.160) and PE (β = 0.176), and PI is positively predicted by AAI (β = 0.327). The model explains $R^2$ = 0.261 (PU), 0.422 (PEOU), 0.158 (AAI), and 0.135 (PI) – moderate for PEOU and low-to-moderate for the remaining constructs.

Table 2 presents the results of reliability testing, convergent validity, and multicollinearity diagnostics for the latent variables in the model.

All items loaded at ≥ 0.712; CA = 0.803–0.878, CR = 0.871–0.920, and AVE = 0.614–0.794, exceeding recommended cut-offs (CA/CR ≥ 0.70; AVE ≥ 0.50). VIF = 1.517–2.706 < 5, indicating no multicollinearity. Hence, the measurement scales demonstrate satisfactory reliability and convergent validity.

Examining discriminant validity among the latent variables is the next stage in assessing the measurement model after reliability and convergent validity have been determined using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), as indicated in Table 2. To make sure that the constructs in the model are comparatively distinct and do not overlap in terms of measurement content, discriminant validity must be established.

The results show that all HTMT values fall within the acceptable threshold. Specifically, the highest value was 0.702 (between T and PE), followed by 0.678 (between T and PEOU) and 0.653 (between

**Table 2.** Reliability, convergent validity, and multicollinearity (SmartPLS 4.0)

| Latent variable | No. of items | Outer loadings (range) | Cronbach's Alpha (CA) | Composite Reliability (CR) | AVE | VIF (range) |
|---|---|---|---|---|---|---|
| AAI | 4 | [0.818 – 0.883] | 0.878 | 0.916 | 0.732 | [2.047 – 2.669] |
| PE | 4 | [0.791 – 0.896] | 0.855 | 0.902 | 0.698 | [1.841 – 2.706] |
| PEOU | 4 | [0.749 – 0.881] | 0.847 | 0.897 | 0.687 | [1.560 – 2.413] |
| PI | 5 | [0.712 – 0.819] | 0.842 | 0.888 | 0.614 | [1.667 – 2.690] |
| PU | 4 | [0.782 – 0.815] | 0.803 | 0.871 | 0.629 | [1.517 – 1.843] |
| SN | 3 | [0.866 – 0.908] | 0.870 | 0.920 | 0.794 | [2.114 – 2.536] |
| T | 4 | [0.797 – 0.890] | 0.854 | 0.902 | 0.697 | [1.987 – 2.663] |

**Table 3.** Discriminant validity (HTMT ratios)

| Variable | AAI | PE | PEOU | PI | PU | SN | T |
|---|---|---|---|---|---|---|---|
| AAI | – | – | – | – | – | – | – |
| PE | 0.312 | – | – | – | – | – | – |
| PEOU | 0.289 | 0.176 | – | – | – | – | – |
| PI | 0.385 | 0.169 | 0.522 | – | – | – | – |
| PU | 0.362 | 0.438 | 0.408 | 0.537 | – | – | – |
| SN | 0.353 | 0.653 | 0.463 | 0.185 | 0.284 | – | – |
| T | 0.429 | 0.702 | 0.678 | 0.466 | 0.562 | 0.274 | – |

PE and SN). These values indicate relatively strong associations among constructs that are theoretically related, while still meeting the requirement for discriminant validity. In contrast, pairs of constructs without direct relationships (such as PE-PI or SN-PI) exhibited lower HTMT ratios, confirming clear conceptual distinctions between them.

Thus, before performing the Structural Equation Modeling (SEM) analysis, the measurement scales used in this work meet the criteria for discriminant validity, enhancing the validity and reliability of the measurement model.

**Table 4.** Coefficient of determination ($R^2$) and adjusted $R^2$

| Dependent variable | $R^2$ | Adjusted $R^2$ |
|---|---|---|
| AAI | 0.158 | 0.146 |
| PEOU | 0.422 | 0.416 |
| PI | 0.135 | 0.130 |
| PU | 0.261 | 0.254 |

The coefficient of determination ($R^2$) values range from 0.135 to 0.422, according to the results in Table 4. The model's independent variables explained 42.2% of its variance, which is a moderate level of explanatory power by Hair et al. (2019) standards. Of these, PEOU (Perceived Ease of Use) had the best $R^2$ value (0.422). AAI (Attitude toward AI) and PI (Purchase Intention) had lower $R^2$ values of 0.158 and 0.135, respectively, although PU (Perceived Usefulness) also showed a moderate $R^2$ value of 0.261. These findings are in line with behavioral models in socio-technological situations, indicating a comparatively low but acceptable explanatory capacity.

Furthermore, the model is comparatively stable and unaffected by the number of independent variables, as evidenced by the slight variations in $R^2$ and adjusted $R^2$ values. This strengthens the measurement model's dependability even more and offers a strong basis for carrying out the Structural Equation Modeling (SEM) analysis that follows.

In order to ascertain the relative significance of each relationship in the model, the study first assessed the explanatory power of the model using the $R^2$ coefficients (Table 4). Next, the $f^2$ effect size was used to analyze the individual effects of each independent variable on the dependent variables.

**Table 5.** Effect sizes ($f^2$) for key paths

| Variable | AAI | PE | PEOU | PI | PU | SN | T |
|---|---|---|---|---|---|---|---|
| AAI | – | – | – | 0.119 | – | – | – |
| PE | 0.036 | – | – | – | – | – | – |
| PEOU | 0.028 | – | – | – | – | – | – |
| PI | – | – | – | – | – | – | – |
| PU | 0.033 | – | – | – | – | – | – |
| SN | – | – | 0.121 | – | 0.024 | – | – |
| T | – | – | 0.401 | – | 0.237 | – | – |

Table 5 indicates the strongest incremental contribution is T → PEOU ($f^2 = 0.401$) — a large effect (Cohen, 1988). T → PU ($f^2 = 0.237$) is medium. SN → PEOU ($f^2 = 0.121$) and AAI → PI ($f^2 = 0.119$) fall in the small-to-medium range, showing subjective norm and attitude meaningfully shape ease of use and purchase intention. The remaining paths (PE → AAI = 0.036; PEOU → AAI = 0.028; PU → AAI = 0.033; SN → PU = 0.024) are small, indicating modest but non-negligible incremental contributions consistent with the theoretical model.

Figure 3 presents the results of the PLS-SEM structural model assessment after removing the observed variable AAI1 and refining the model.

Nodes report $R^2$ (PU = 0.261; PEOU = 0.422; AAI = 0.158; PI = 0.135). The numbers on paths are p-values, indicating that all hypothesized relations are statistically significant: T → PU ($p < 0.001$), T

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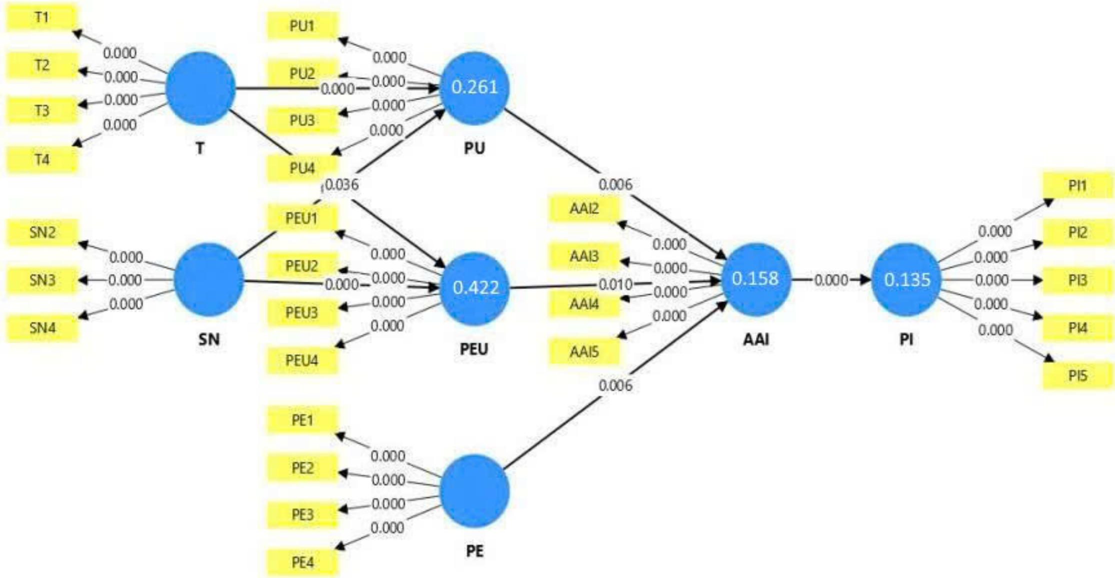


**Figure 3.** Structural model results (PLS-SEM)

→ PEOU ($p < 0.001$), SN → PU ($p < 0.001$), SN → PEOU ($p < 0.001$), PU → AAI ($p = 0.006$), PEOU → AAI ($p = 0.010$), PE → AAI ($p = 0.006$), and AAI → PI ($p < 0.001$). Corresponding standardized coefficients (β) and inference are reported in Table 6, while incremental contributions ($f^2$) appear in Table 5. Overall, the model shows moderate explanatory power for PEOU and small-to-moderate for the remaining constructs, providing consistent support for *H1-H8*.

The path coefficients between the latent variables were computed and shown based on Figure 3, which shows the findings of the structural model evaluation. This enabled to clearly identify the direction and amplitude of the linkages in the research model. The results of the hypothesis testing for *H1-H8* are shown in Table 6 to give a more thorough explanation of these coefficients and to evaluate the statistical significance of each association.

All eight hypotheses (H1-H8) are supported ($p < 0.05$). Upstream drivers – Trust (T) and Subjective Norm (SN) – positively affect cognitive beliefs: T → PEOU ($\beta = 0.504$, $p < 0.001$), T → PU ($\beta = 0.435$, $p < 0.001$), SN → PU ($\beta = 0.504$, $p < 0.001$), SN → PEOU ($\beta = 0.275$, $p = 0.036$). Regarding the attitudinal mechanism, PU ($\beta = 0.186$, $p = 0.006$), PEOU ($\beta = 0.160$, $p = 0.010$), and PE ($\beta = 0.176$, $p = 0.006$) increase AAI, and AAI predicts PI ($\beta = 0.327$, $p < 0.001$).

Table 7 presents the results of the specific mediation tests, clarifying the mediating role of AAI in the relationship between the independent variables and purchase intention.

The findings support the mediating function of PU, PEOU, and AAI in the model by showing that the majority of indirect associations are statistically significant (*H9, H10, H11, H13, H14*, and *H15*). Interestingly, the most substantial in-

**Table 6.** Direct effects and hypothesis tests (*H1-H8*)

| Hypothesis | Relationship | Path coefficient (O) | Sample mean (M) | Standard deviation (STDEV) | t-value (\|O/STDEV\|) | p-value | Result |
|---|---|---|---|---|---|---|---|
| *H1* | T → PU | 0.435 | 0.437 | 0.062 | 8.129 | 0.000 | Supported |
| *H2* | T → PEOU | 0.504 | 0.506 | 0.053 | 5.189 | 0.000 | Supported |
| *H3* | SN → PU | 0.504 | 0.505 | 0.062 | 7.016 | 0.000 | Supported |
| *H4* | SN → PEOU | 0.275 | 0.276 | 0.059 | 4.424 | 0.036 | Supported |
| *H5* | PU → AAI | 0.186 | 0.187 | 0.068 | 2.353 | 0.006 | Supported |
| *H6* | PEOU → AAI | 0.160 | 0.161 | 0.062 | 3.000 | 0.010 | Supported |
| *H7* | PE → AAI | 0.176 | 0.178 | 0.063 | 2.793 | 0.006 | Supported |
| *H8* | AAI → PI | 0.327 | 0.328 | 0.055 | 5.945 | 0.000 | Supported |

**Table 7.** Specific indirect effects (*H9-H15*)

| Relationship | Path coefficient (O) | Mean (M) | Standard deviation (STDEV) | t-statistic (\|O/STDEV\|) | p-value | Result |
|---|---|---|---|---|---|---|
| T → PU → AAI | 0.081 | 0.082 | 0.033 | 2.455 | 0.014 | Supported H9 |
| T → PEOU → AAI | 0.081 | 0.081 | 0.035 | 2.314 | 0.021 | Supported H10 |
| SN → PU → AAI | 0.094 | 0.094 | 0.019 | 4.947 | 0.000 | Supported H11 |
| SN → PEOU → AAI | 0.044 | 0.044 | 0.029 | 1.517 | 0.130 | Not Supported H12 |
| PU → AAI → PI | 0.061 | 0.053 | 0.028 | 2.179 | 0.027 | Supported H13 |
| PEOU → AAI → PI | 0.052 | 0.063 | 0.024 | 2.179 | 0.030 | Supported H14 |
| PE → AAI → PI | 0.058 | 0.060 | 0.023 | 2.522 | 0.012 | Supported H15 |

**Table 8.** Total/overall effects on AAI and PI

| Relationship | Path coefficient (O) | Mean (M) | Standard deviation (STDEV) | t-statistics (\|O/STDEV\|) | p-values |
|---|---|---|---|---|---|
| PE → PI | 0.058 | 0.060 | 0.023 | 2.522 | 0.012 |
| PEOU → PI | 0.053 | 0.055 | 0.024 | 2.208 | 0.028 |
| PU → PI | 0.062 | 0.064 | 0.028 | 2.214 | 0.027 |
| SN → AAI | 0.045 | 0.045 | 0.019 | 2.368 | 0.018 |
| SN → PI | 0.015 | 0.016 | 0.007 | 2.143 | 0.033 |
| T → AAI | 0.162 | 0.171 | 0.040 | 4.050 | 0.000 |
| T → PI | 0.053 | 0.059 | 0.019 | 2.789 | 0.005 |

direct effect is seen via the path SN → PU → AAI. *H12* (SN → PEOU → AAI), on the other hand, is not supported, indicating that PU, not PEOU, is the primary mechanism by which SN influences AAI.

All effects in Table 8 are statistically significant ($p < 0.05$). The upstream factors exhibit both direct and indirect influences: Trust (T) exerts the strongest effect on AAI (O = 0.162, t = 4.050, $p < 0.001$) and a small direct effect on PI (O = 0.053, t = 2.789, p = 0.005). The cognitive/experiential beliefs – PE → PI (O = 0.058, p = 0.012), PEOU → PI (O = 0.053, p = 0.028), and PU → PI (O = 0.062, p = 0.027) – are positive but modest, reinforcing AAI as the primary mediating mechanism. SN has positive effects on AAI (O = 0.045, p = 0.018) and PI (O = 0.015, p = 0.033). Overall, T and SN shape PI both directly and indirectly through PU/PEOU and AAI, with the T → AAI pathway being the most prominent.

All direct hypotheses *H1-H8* are supported (Table 6). Specific and overall mediation (Tables 7-8) confirm AAI as the key mediator linking PU/PEOU/PE to PI, with notable upstream effects from Trust and Subjective Norms via PU. The pattern underscores a cognition-led route (usefulness and ease) reinforced by experiential enjoyment.

# 4. DISCUSSION

This study shows that Trust (T) and Subjective Norm (SN) are foundational in shaping consumers' cognitive appraisals of AI in e-commerce. Both Perceived Usefulness (PU; beta = 0.435, $p < 0.001$) and Perceived Ease of Use (PEOU; beta = 0.504, $p < 0.001$) are strongly predicted by Trust. This means that platform integrity and stability lower uncertainty, making AI features feel easier and more useful to use. This aligns with trust-based accounts in online contexts (Gefen et al., 2003; Pavlou & Gefen, 2004) and recent evidence in AI in shopping settings (Nguyen et al., 2024a). Also, SN has a positive effect on PU (beta = 0.504, $p < 0.001$) and PEOU (beta = 0.275, p = 0.036), which is in line with TPB and TAM extensions that show normative pressure increases views about the value of technology and the amount of work that people are willing to put in (Ajzen, 1991; Sharma et al., 2016; Venkatesh & Davis, 2000).

TAM paths are also supported: PU (beta = 0.186, p = 0.006) and PEOU (beta = 0.160, p = 0.010) increase Attitude toward AI (AAI), while Perceived Enjoyment (PE) adds an affective pathway (beta = 0.176, p = 0.006). This confirms that both cognitive appraisals and hedonic experience shape attitudes (Davis, 1989; Tussyadiah, 2020; Van der Heijden, 2004). AAI, in turn, strongly predicts purchase in-


http://dx.doi.org/10.21511/im.21(4).2025.22

tention (PI; beta = 0.327, $p < 0.001$), echoing findings that attitude is the proximal driver of technology-enabled consumer behavior (Dai & Liu, 2024).

Mediation results clarify the mechanisms. Indirect effects via PU and PEOU are largely supported (*H9, H10, H11, H13-H15*), establishing TAM constructs and AAI as key conduits through which trust, social influence, and enjoyment influence PI. Notably, *H12* (SN → PEOU → AAI) is not supported (beta = 0.044, p = 0.130), suggesting that normative cues shape attitudes mainly by strengthening usefulness beliefs (SN → PU → AAI) rather than ease perceptions. This nuance extends prior work by showing that in AI-mediated shopping, social endorsement translates into perceived benefits more than perceived effort reduction (Laudon & Traver, 2021; Van der Heijden, 2004; Wilson et al., 2021).

Overall, these patterns integrate TPB and TAM perspectives: social and trust antecedents mould cognitive (PU, PEOU) and affective (PE) evaluations, which form AAI and ultimately PI. The results reinforce established theory (Ajzen, 1991; Davis, 1989; Venkatesh & Davis, 2000) while adding evidence from an AI-intensive, emerging-market context.

## CONCLUSION

This study aimed to investigate how core cognitive, psychosocial, and hedonic factors shape consumers' attitudes toward AI and how these attitudes influence online purchase intentions in AI-enabled e-commerce.

The results confirmed that trust and subjective norm significantly enhanced consumers' perceptions of usefulness and ease of use; these perceptions, together with perceived enjoyment, strengthened attitudes toward AI. Attitude was found to be the strongest predictor of purchase intention, mediating the influence of upstream variables. These findings validated an extended TAM/TPB framework tailored to Vietnam's digital retail context.

From these results, we conclude that trust and social endorsement play a foundational role in shaping perceptions of AI technologies, while perceived enjoyment provides additional affective lift. Building confidence, demonstrating clear value, and enhancing the user experience through engaging, intuitive AI interactions should be top priorities for businesses. In the future, this model should be tested with larger groups of people, and more variables, such as perceived risk or fairness, should be incorporated. Additionally, longitudinal or experimental methods should be used to examine how views change over time.

## AUTHOR CONTRIBUTIONS

Conceptualization: Le Thi Kim Hoa.
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## ACKNOWLEDGMENT

The author sincerely thanks all the respondents who participated in the survey. Besides, heartfelt gratitude is extended to all stakeholders for their valuable support and assistance, which made a significant contribution to the completion of this research.

## AI STATEMENT

The author confirms that no Generative AI or AI-based tools were used in the writing, analysis, or revision of this manuscript. All content was produced and validated solely by the author.

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