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THE IMPACT OF AI-DRIVEN PERSONALIZED ADVERTISING ON CONSUMER PURCHASE INTENTION: EVIDENCE FROM SHOPEE USERS IN HO CHI MINH CITY

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ABSTRACT

Artificial intelligence (AI)-enabled personalized advertising has become a critical strategy for enhancing customer engagement in digital commerce. However, the psychological mechanisms through which perceived personalization translate into purchase intention remain insufficiently understood. Drawing on the Stimulus–Organism–Response (S–O–R) framework, this study examines how AI-enabled perceived personalization influences purchase intention through perceived relevance, perceived usefulness, and perceived trust. A quantitative survey was conducted with 520 Shopee users who had previously been exposed to AI-enabled personalized advertising, and the proposed model was analyzed using partial least squares structural equation modeling (PLS-SEM). The findings indicate that perceived personalization significantly enhances perceived relevance, perceived usefulness, and perceived trust, while its direct effect on purchase intention is insignificant. Instead, purchase intention is primarily driven through indirect cognitive pathways, with perceived usefulness emerging as the strongest predictor of consumers' purchase intention. These findings suggest that the effectiveness of AI-enabled personalized advertising depends less on algorithmic sophistication itself than on consumers' evaluations of its relevance, utility, and trustworthiness. This study extends the S–O–R literature by providing an integrated explanation of the cognitive mechanisms linking AI-enabled perceived personalization and purchase intention within an emerging e-commerce market. The findings also offer practical implications for digital retailers seeking to design AI-enabled advertising strategies that create meaningful customer value and strengthen purchase intention.

Keywords: AI, advertising, consumer perceptions, Shopee, Ho Chi Minh City.

1. INTRODUCTION

Artificial intelligence (AI) has transformed digital advertising by enabling large-scale, algorithmically mediated personalization [1]. In competitive e-commerce environments, AI-powered personalization has become a strategic approach for capturing consumer attention and improving conversion performance [2], [3]. By leveraging predictive analytics and real-time behavioral data, AI dynamically tailors advertising content to individual consumers, thereby enhancing message precision and increasing the likelihood of purchase intention [4].

Despite its growing strategic importance, the psychological processes through which AI-driven personalization influences consumer decision-making remain insufficiently understood. Rather than assuming a direct relationship between personalization and behavioral outcomes, this study adopts the Stimulus–Organism–Response (S–O–R) framework by conceptualizing AI-enabled personalization as an external stimulus that elicits consumers' internal evaluations, namely perceived trust [5], perceived relevance [6]–[8], and perceived usefulness [9], [10]. These organismic evaluations represent the cognitive processes through which personalized advertising influences consumers' purchase decisions.

However, two important research gaps remain. First, previous studies have primarily examined perceived trust, perceived relevance, and perceived usefulness as separate explanatory mechanisms, resulting in a fragmented understanding of the cognitive processes underlying consumers' responses to AI-enabled personalized advertising [11], [12]. Although each construct has been shown to influence behavioral outcomes, existing research provides limited insight into how these organismic evaluations jointly explain the psychological mechanism through which perceived personalization is translated into purchase intention. Second, empirical evidence has been derived predominantly from developed economies [13], [14], limiting the contextual generalizability of existing findings. Differences in digital maturity, consumer trust in AI technologies, and e-commerce adoption may shape consumers' responses to personalized advertising in emerging markets, yet this issue remains insufficiently examined.

To address these research gaps, this study develops and empirically validates an integrated S–O–R framework that explains the cognitive mechanism linking AI-enabled personalization to purchase intention among Shopee users in Ho Chi Minh City.

This study makes three contributions to literature. First, it extends the S–O–R framework by explaining the cognitive mechanism through which AI-enabled personalization is transformed into purchase intention, thereby moving beyond the fragmented examination of individual cognitive evaluations. Second, it enriches the personalization literature by providing evidence from an emerging e-commerce market, extending the contextual applicability of existing knowledge beyond developed economies. Third, it offers managerial insights into how digital retailers can strengthen consumers' trust, relevance perceptions, and perceived usefulness to maximize the effectiveness of AI-driven personalized advertising.

2. LITERATURE REVIEW

2.1. Theoretical background

2.1.1. The S-O-R paradigm and AI-Driven personalized advertising

This study adopts the Stimulus–Organism–Response (S–O–R) paradigm as its underlying theoretical framework. Within this framework, AI-driven personalized advertising functions as the external technological stimulus (S), referring to the algorithmic personalization of advertising content and product recommendations based on consumers' behavioral data and predictive analytics [1], [2].

The technological stimulus elicits consumers' internal organismic evaluations (O), namely perceived relevance, perceived usefulness, and perceived trust. These cognitive evaluations explain how consumers interpret and evaluate AI-enabled personalized advertising before forming behavioral responses. Accordingly, purchase intention represents the behavioral response (R) in the proposed research framework.

2.1.2. Conceptual definitions of key constructs

Perceived Personalization refers to consumers' perception that advertising content is tailored to their individual preferences, needs, and prior interactions with the platform [15].

Perceived Relevance refers to consumers' evaluation that advertising content is personally meaningful and consistent with their current needs and interests [16].

Perceived Usefulness refers to consumers' belief that personalized advertising facilitates purchase decision-making by reducing search effort and improving shopping efficiency [17].

Perceived Trust refers to consumers' confidence in the competence, integrity, and benevolence of the AI-enabled recommendation system and the platform delivering personalized advertising [18].

Purchase Intention refers to consumers' willingness to purchase products or services following exposure to AI-driven personalized advertising [19]

2.2. Hypothesis development

2.2.1. Perceived Personalization

Perceived personalization refers to consumers' perception that advertising content is tailored to their individual preferences, needs, and prior interactions with the platform [15]. Within the S–O–R framework, perceived personalization represents the external technological stimulus that shapes consumers' cognitive evaluations of AI-driven personalized advertising. By increasing the congruence between advertising content and consumers' individual preferences, personalized advertising enhances the perceived relevance of advertising messages to consumers' immediate needs and purchase goals. Greater message–consumer congruence facilitates information processing and enables consumers to evaluate advertising content as more meaningful and applicable to their decision context [7], [16], [20].

Perceived personalization also contributes to the development of consumer trust. Personalized recommendations demonstrate that firms recognize consumers' preferences and provide information aligned with their individual needs. Such personalized interactions signal organizational competence, responsiveness, and customer orientation, thereby reducing perceptions of opportunistic selling and strengthening consumers' confidence in both the platform and its AI-enabled recommendation system [21]–[23].

In addition, perceived personalization enhances the functional value of advertising by filtering irrelevant information and presenting products that better match consumers' shopping objectives. By reducing search effort and simplifying product evaluation, AI-driven personalized advertising increases consumers' perceptions that the recommended information is useful for supporting purchase decisions [24], [25].

Beyond shaping consumers' cognitive evaluations, perceived personalization may also directly influence purchase intention. Personalized advertising creates a more engaging and individually relevant shopping experience, thereby increasing consumers' willingness to purchase the recommended products or services [26], [27].

H1: Perceived personalization exerts a positive effect on consumers' perceived relevance.

H2: Perceived personalization exerts a positive effect on consumers' perceived trust.

H3: Perceived personalization exerts a positive effect on consumers' perceived usefulness.

H4: Perceived personalization exerts a positive effect on consumers' purchase intention.

2.2.2. Perceived Relevance

Perceived relevance refers to consumers' evaluation that advertising content is personally meaningful and consistent with their current needs and interests [16]. Within AI-driven personalized advertising, relevant messages reduce perceptions of intrusiveness and increase consumers' confidence that the platform accurately understands their preferences. Such cognitive evaluations strengthen perceptions of competence and responsible data use, thereby enhancing perceived trust [28]–[30].

Relevant advertising also facilitates purchase decisions by reducing cognitive effort and improving evaluation efficiency. When advertising aligns with consumers' purchase goals, they are more likely to accept AI-generated recommendations and develop stronger purchase intentions [6], [31].

H5: Consumers' perceived relevance exerts a positive effect on their perceived trust.

H6: Consumers' perceived relevance exerts a positive effect on their purchase intention.

2.2.3. Perceived Usefulness

Mục Perceived relevance refers to consumers' evaluation that advertising content is personally meaningful and consistent with their current needs and interests [16]. Within AI-driven personalized advertising, relevant messages reduce perceptions of intrusiveness and increase consumers' confidence that the platform accurately understands their preferences. Such cognitive evaluations strengthen perceptions of competence and responsible data use, thereby enhancing perceived trust [28]-[30].

Relevant advertising also facilitates purchase decisions by reducing cognitive effort and improving evaluation efficiency. When advertising aligns with consumers' purchase goals, they are more likely to accept AI-generated recommendations and develop stronger purchase intentions [6], [31].

H7: Consumers' perceived trust exerts a positive effect on their perceived usefulness

H8: Consumers' perceived usefulness exerts a positive effect on their purchase intention.

2.2.4. Perceived Trust

Perceived trust refers to consumers' confidence in the competence, integrity, and benevolence of the AI-enabled recommendation system and the platform delivering personalized advertising [18]. In AI-mediated e-commerce, algorithmic opacity and privacy concerns increase uncertainty during purchase decisions. Trust mitigates these concerns by strengthening consumers' confidence in AI-generated recommendations and reducing perceived transactional risk. As a result, consumers are more likely to rely on personalized recommendations and develop stronger purchase intentions [18], [36]–[39].

H9: Consumers' perceived trust exerts a positive effect on their purchase intention.

2.2.5. Conceptual Framework

Anchored in the S–O–R paradigm, this study advances a conceptual framework where

Anchored in the S–O–R paradigm, the proposed framework conceptualizes perceived personalization as the technological stimulus (S), while perceived relevance, perceived usefulness, and perceived trust represent the organismic evaluations (O) through which consumers process AI-driven personalized advertising before forming purchase intention (R).

Although prior studies have reported positive relationships between trust, perceived value, and online purchase intention [36], [40], evidence remains fragmented regarding the cognitive mechanisms underlying AI-driven personalized advertising. In particular, limited research has examined the integrated roles of perceived relevance, perceived usefulness, and perceived trust within a unified S–O–R framework in Vietnam's AI-enabled e-commerce context [41]. By addressing this gap, the proposed model provides a more comprehensive explanation of consumers' purchase intention toward AI-driven personalized advertising.

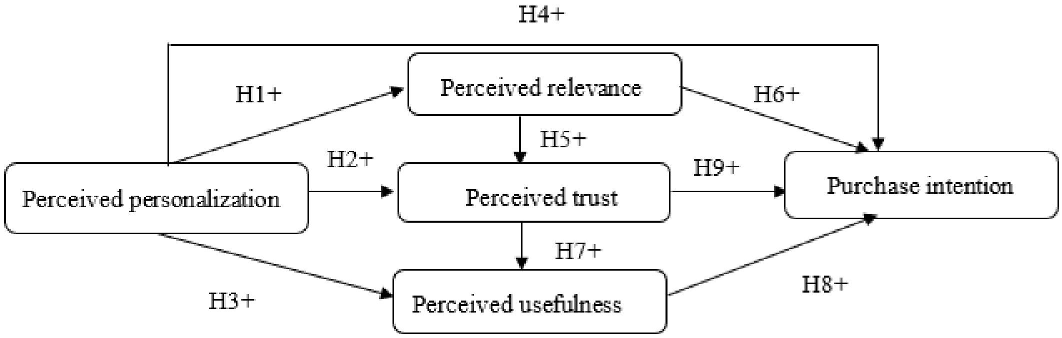

Figure 1. Theoretical framework.

Source: Author, 2025

3. METHODOLOGY

3.1. Instrument development

A structured questionnaire adapted from established measurement scales [42]–[47] was employed for data collection and refined to reflect the Shopee context. The questionnaire comprised three sections. The first included screening questions to confirm respondents' prior exposure to AI-driven personalized advertising. The second collected demographic and digital usage information. The third measured the research constructs using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The measurement scales included perceived personalization (5 items) [43], perceived relevance (4 items) [45], [46], perceived trust (5 items) [48], [49], perceived usefulness (5 items) [42], and purchase intention (5 items) [45]. To improve contextual appropriateness, the instrument was reviewed through expert evaluation before formal data collection. Employing previously validated scales supports measurement reliability and construct validity in PLS-SEM research.

3.2. Qualitative validation

To establish content validity, the questionnaire was reviewed through qualitative expert evaluation before the main survey. Between November 1 and 5, 2025, semi-structured interviews were conducted with five experts, including two senior Shopee e-commerce managers and three academics specializing in e-commerce from Ho Chi Minh City University of Industry and Trade. Minor wording revisions were made based on their feedback to improve clarity and contextual suitability for the Vietnamese e-commerce environment.

3.3 Sampling and data collection

A non-probability convenience sampling approach was adopted to recruit active Shopee users [50]. The online questionnaire was distributed via Facebook and Zalo over four weeks from November 8 to December 8, 2025. Screening questions ensured that respondents had recently been exposed to AI-driven personalized product recommendations on Shopee.

Following data collection, responses were screened for incompleteness, straight-lining, logical inconsistency, and unusually short completion times. After data cleaning, 520 valid responses were retained for analysis. This sample exceeded the recommended minimum for PLS-SEM based on the 10-times rule, indicating adequate statistical power for estimating the proposed structural model [48].

3.4. Data Analysis

Data were analyzed using SmartPLS 4 following the two-stage PLS-SEM procedure recommended in the literature [51]. PLS-SEM was selected because the proposed model incorporates multiple mediation relationships and emphasizes prediction and variance explanation [51].

The measurement model was evaluated through indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), the Fornell–Larcker criterion, HTMT ratios, and outer variance inflation factors (VIF). Common method bias was addressed through procedural remedies, including respondent anonymity and questionnaire design, and statistically assessed using full collinearity VIF and the marker-variable technique [49].

The structural model was subsequently evaluated using bootstrapping with 5,000 resamples. Path coefficients, coefficients of determination (R^2), and predictive relevance (Q^2) were examined to assess the explanatory and predictive performance of the proposed model.

4. RESULTS AND DISCUSSION

4.1. Sample characteristics

The final sample comprised 520 valid responses from Shopee users who had previously been exposed to AI-driven personalized advertising. The respondents represented a diverse demographic profile in terms of age, income, and digital engagement, providing adequate variation for examining consumer responses to AI-driven personalized advertising in Vietnam's e-commerce context. A detailed demographic summary is presented in Table 1.

Table 1. Sample Characteristics

Demographic Variable	Category	Frequency (n=520)	Percentage (%)
Gender	Male	189	36.35
	Female	295	56.73
	Others	36	6.92
Age	18–22 years old	97	18.65
	23–27 years old	106	20.38
	28–32 years old	162	31.15
	Over 32 years old	155	29.81
Income/ monthly (VND)	Under 5 million	101	19.42
	5 - under 10 million	143	27.5
	10 - under 15 million	152	29.23
	15 under 20 million	104	20
	20 million and above	20	3.85
Average amount spent per online purchase	< 200,000 VND	83	15.96
	200,000 VND - <400,000 VND	185	35.58
	400,000 VND - < 600,000 VND	101	19.42

	600,000 VND - < 800,000 VND	120	23.08
	From 800,000 VND onwards	31	5.96
Online Shopping Frequency	Once a week	127	24.42
	2–3 times a week	181	34.81
	4–5 times a week	137	26.35
	More than 5 times a week	75	14.42

Source: Author, 2025

The sample (n = 520) exhibits adequate demographic and behavioral diversity. Female respondents accounted for 56.73% of the sample, while most participants were economically active adults, with the largest age groups being 28–32 years (31.15%) and over 32 years (29.81%). Respondents were predominantly middle-income consumers, and most reported moderate online spending (200,000–400,000 VND per purchase) together with frequent online shopping, typically two to three times per week. These characteristics indicate that the sample is well suited for examining consumers' responses to AI-driven personalized advertising in Shopee's e-commerce environment. Detailed descriptive statistics are reported in Table 1.

4.2. Measurement model assessment

4.2.1. Indicator reliability and internal consistency reliability

The measurement model was evaluated before structural model assessment to establish the reliability and quality of the measurement scales. Indicator reliability was assessed using outer loadings, whereas internal consistency reliability was examined through Cronbach's alpha and composite reliability. Outer variance inflation factors (VIF) were additionally inspected to detect potential multicollinearity among indicators. The results are reported in Table 2.

Table 2. Indicator reliability and internal consistency assessment

Constructs	Items	Loadings	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Outer VIF
Perceived Personalization (PP)	PP1: "AI-powered personalized advertising on digital platforms makes purchase recommendations that match my needs."	0.789	0.849	0.855	0.892	1.746
	PP2: "AI-powered personalized advertising on digital platforms enables me to order products that are tailor-made for me."	0.825				1.935
	PP3: "AI-powered personalized advertising on digital platforms is customized to my needs."	0.815				1.904
	PP4: "Overall, AI-powered personalized advertising on digital platforms is tailored to my situation."	0.787				1.821

	PP5: Overall, personalized advertising based on artificial intelligence on digital platforms is designed to suit my preferences.	0.730				1.562
Perceived Relevance (PR)	PR1: "AI-powered personalized advertising on digital platforms seems important to me."	0.815	0.805	0.807	0.872	1.673
	PR2: "AI-powered personalized advertising on digital platforms is meaningful to me."	0.790				1.611
	PR3: "AI-powered personalized advertising on digital platforms fits with my preferences."	0.808				1.714
	PR4: "Overall, AI-powered personalized advertising on digital platforms fits me."	0.761				1.528
Perceived Trust (PT)	PT1: "AI-powered personalized advertising on digital platforms has integrity."	0.805	0.871	0.871	0.906	1.865
	PT2: "AI-powered personalized advertising on digital platforms is reliable."	0.819				1.997
	PT3: "AI-powered personalized advertising on digital platforms is trustworthy."	0.799				1.916
	PT4: "I can trust AI-powered personalized advertising on digital platforms."	0.830				2.109
	PT5: "I highly trust AI-powered personalized advertising on digital platforms."	0.806				1.915
Perceived Usefulness (PU)	PU1: "AI-powered personalized advertising on digital platforms saves me time when shopping."	0.805	0.848	0.850	0.892	1.807
	PU2: "AI-powered personalized advertising on digital platforms supports important aspects of my shopping."	0.786				1.761
	PU3: "AI-powered personalized advertising on	0.763				1.671

	digital platforms helps me improve my shopping efficiency.”					
	PU4: “AI-powered personalized advertising on digital platforms enhances the quality of my shopping experience.”	0.794				1.778
	PU5: “Personalized advertising based on artificial intelligence on digital platforms increases my shopping interest.”	0.795				1.794
	PI1: “I will buy products that are advertised through AI-powered personalized advertising on digital platforms.”	0.776				1.834
	PI2: “I desire to buy products that are promoted through AI-powered personalized advertising on digital platforms.”	0.775				1.772
Purchase Intention (PI)	PI3: “I am likely to buy products that are promoted through AI-powered personalized advertising on digital platforms.”	0.804	0.859	0.864	0.899	1.895
	PI4: “I plan to purchase products that are promoted through AI-powered personalized advertising on digital platforms”	0.830				2.000
	PI5: “In the future, when I need to shop, I will buy products that are advertised through personalized, AI-powered advertising on digital platforms”.	0.811				1.949

Source: Author, 2025

The measurement model satisfied the recommended reliability criteria (Table 2). Outer loadings ranged from 0.730 to 0.830, indicating satisfactory indicator reliability for all measurement items [52]. Internal consistency was supported by Cronbach's alpha (0.805–0.871) and composite reliability (0.807–0.871), both exceeding the recommended threshold of 0.70 [53], [54]. In addition, outer VIF values ranged from 1.528 to 2.109, remaining well below the threshold of 5.0 and indicating no evidence of multicollinearity among the indicators [55].

4.2.2. Convergent and discriminant validity

The measurement model demonstrated satisfactory convergent and discriminant validity. As reported in Table 3, AVE values ranged from 0.622 to 0.659, exceeding the recommended threshold of 0.50 [56]. Discriminant validity was further supported by the Fornell–Larcker criterion (Table 4), where the square root of each construct's AVE exceeded its correlations with other constructs, and by HTMT ratios ranging from 0.553 to 0.879 (Table 5), all below the recommended cutoff of 0.90 [57]. These results confirm the construct validity of the proposed measurement model.

Table 3. Construct Convergent Validity

Constructs	AVE
PI	0.639
PP	0.624
PR	0.630
PT	0.659
PU	0.622

Source: Author, 2025

Discriminant validity was further established using the Fornell–Larcker criterion (Table 4) [58]. The square roots of the AVE, ranging from 0.789 to 0.812, consistently exceeded all corresponding inter-construct correlations, demonstrating that each latent construct exhibited stronger associations with its own indicators than with other constructs. These results provide robust evidence that the measurement model possesses adequate discriminant validity.

Table 4. Fornell-Larcker Criterion.

	PI	PP	PR	PT	PU
PI	0.800				
PP	0.280	0.790			
PR	0.433	0.280	0.794		
PT	0.257	0.430	0.265	0.812	
PU	0.607	0.359	0.500	0.288	0.789

Source: Author, 2025

Discriminant validity was further established using the Heterotrait–Monotrait (HTMT) ratio (Table 5). HTMT values ranged from 0.553 to 0.879, remaining consistently below the recommended threshold of 0.90 [57]. These findings provide robust evidence that the latent constructs are empirically distinct, indicating minimal conceptual overlap and confirming that the measurement model possesses satisfactory discriminant validity.

Table 5. Heterotrait-Monotrait (HTMT) Ratio

	PI	PP	PR	PT	PU
PI					
PP	0.323				
PR	0.516	0.336			
PT	0.296	0.497	0.315		
PU	0.705	0.420	0.602	0.336	

Source: Author, 2025

Collectively, the Fornell–Larcker and HTMT assessments provide convergent evidence that the latent constructs are both conceptually and empirically distinct, thereby establishing robust discriminant validity and reinforcing the overall adequacy of the measurement model.

4.3. Structural model assessment

4.3.1. Assessment of common method bias

To examine the potential influence of common method bias (CMB), the study employed both the full collinearity assessment and the marker-variable technique [52]. The inclusion of the marker variable produced only negligible reductions in the explanatory power of the endogenous constructs, with the R^2 values changing from 0.396 to 0.391 for purchase intention, 0.078 to 0.076 for perceived relevance, 0.207 to 0.204 for perceived trust, and 0.151 to 0.147 for perceived usefulness. All variations remained well below the recommended 10% threshold [59], suggesting that common method bias is unlikely to pose a substantial threat to the validity of the estimated relationships

4.3.2. Hypothesis testing

The structural relationships were assessed using the bootstrapping procedure with 5,000 resamples. As presented in Table 6 and Figure 2**,** seven of the nine hypothesized relationships were statistically supported, providing substantial support for the proposed S–O–R framework.

Perceived personalization emerged as a significant antecedent of all three organism variables. Specifically, it positively influenced perceived relevance (H_1: $\beta = 0.280$, $p < 0.001$), perceived trust (H_2: $\beta = 0.386$, $p < 0.001$), and perceived usefulness (H_3: $\beta = 0.288$, $p < 0.001$). However, its direct effect on purchase intention was not statistically significant (H_4: $\beta = 0.032$, $p = 0.411$), suggesting that the influence of perceived personalization on behavioral intention is primarily indirect rather than direct.

Among the organism variables, perceived relevance significantly enhanced both perceived trust (H_5: $\beta = 0.157$, $p < 0.001$) and purchase intention (H_6: $\beta = 0.159$, $p < 0.001$). Likewise, perceived usefulness positively affected perceived trust (H_7: $\beta = 0.165$, $p < 0.001$) and exerted the strongest direct influence on purchase intention (H_8: $\beta = 0.500$, $p < 0.001$), highlighting its central role in shaping consumers' purchase decisions.

Contrary to expectations, perceived trust did not significantly predict purchase intention (H_9: $\beta = 0.057$, $p = 0.180$). This finding indicates that, within the context of AI-driven personalized advertising on Shopee, trust alone may be insufficient to directly translate into consumers' purchase intention once perceived relevance and perceived usefulness are taken into account.

Table 6. Hypothesis Testing Result.

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Conclusion
H1: PP -> PR	0.280	0.282	0.040	7.025	0.000	Accept
H2: PP -> PT	0.386	0.388	0.041	9.314	0.000	Accept
H3: PP -> PU	0.288	0.290	0.043	6.620	0.000	Accept
H4: PP -> PI	0.032	0.033	0.039	0.823	0.411	Reject
H5: PR -> PT	0.157	0.159	0.041	3.785	0.000	Accept
H6: PR -> PI	0.159	0.159	0.040	3.993	0.000	Accept
H7: PT -> PU	0.165	0.166	0.042	3.926	0.000	Accept
H8: PU -> PI	0.500	0.502	0.046	10.950	0.000	Accept
H9: PT -> PI	0.057	0.057	0.042	1.341	0.180	Reject

Source: Author, 2025

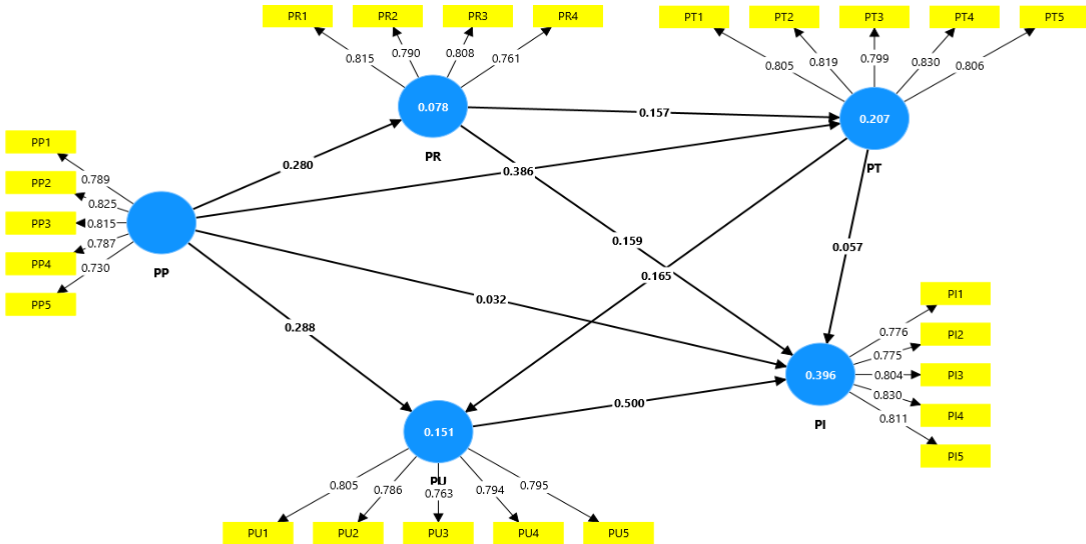

Figure 2. PLS-SEM analytical results

Source: Author, 2025

4.3.3. Predictive power and model evaluation

The structural model was further assessed in terms of its explanatory power (R^2) and predictive relevance (Q^2) following established PLS-SEM guidelines [51], [60]. The model explained 39.6% of the variance in purchase intention ($R^2 = 0.396$; adjusted $R^2 = 0.391$), indicating a moderate level of explanatory power. The remaining endogenous constructs exhibited lower explained variance, with R^2 values of 0.207 for perceived trust, 0.151 for perceived usefulness, and 0.078 for perceived relevance, suggesting that additional factors beyond the proposed model likely influence these cognitive evaluations.

Predictive relevance was examined using the blindfolding procedure. All endogenous constructs yielded positive Q^2 values, confirming that the model possesses satisfactory out-of-sample predictive capability. Purchase intention exhibited the highest predictive relevance ($Q^2 = 0.246$), followed by perceived trust ($Q^2 = 0.134$), perceived usefulness ($Q^2 = 0.091$), and perceived relevance ($Q^2 = 0.047$). Taken together, the R^2 and Q^2 results demonstrate that the proposed model provides an adequate balance between explanatory power and predictive relevance, supporting the robustness of the structural model.

Table 8. R^2 and Q^2 results

	R^2	R^2 adjusted	SSO	SSE	Q^2 (=1-SSE/SSO)
PI	0.396	0.391	2600.000	1959.334	0.246
PR	0.078	0.076	2080.000	1982.576	0.047
PT	0.207	0.204	2600.000	2251.433	0.134
PU	0.151	0.147	2600.000	2363.356	0.091

Source: Author, 2025

5. CONCLUSION

5.1. Main findings

This study advances the understanding of AI-driven personalized advertising by demonstrating that its influence on purchase intention is primarily indirect, operating through consumers' cognitive evaluations rather than through a direct persuasive mechanism. Integrating the Theory of Planned Behavior (TPB) [61], the Technology Acceptance Model (TAM) [42], and digital trust theory [62], the findings indicate that perceived personalization significantly enhances perceived relevance, perceived usefulness, and perceived trust, while exerting no significant direct effect on purchase intention. This suggests that personalization alone is insufficient to stimulate purchasing behavior unless it generates meaningful cognitive value for consumers.

Among the proposed cognitive mechanisms, perceived usefulness emerged as the strongest predictor of purchase intention, followed by perceived relevance, whereas perceived trust did not exert a significant direct effect. These findings indicate that consumers evaluate AI-driven personalized advertising primarily according to its ability to facilitate decision making and deliver contextually relevant information, rather than the sophistication of the personalization technology itself. Overall, the results reinforce the proposition that AI personalization creates behavioral value by enhancing consumers' cognitive appraisal of advertising content rather than acting as an independent behavioral driver.

5.2. Theoretical contributions

This study contributes to literature in several important respects.

First, it extends personalization theory by demonstrating that AI-driven personalization functions as an upstream cognitive stimulus rather than as a direct determinant of purchase intention. Unlike conventional personalization research that frequently reports direct behavioral effects, the present findings indicate that personalization influences consumer behavior only through perceived relevance and perceived usefulness. This finding shifts theoretical attention from algorithmic sophistication to consumers' cognitive evaluation of personalized advertising.

Second, the study extends the Technology Acceptance Model to AI-enabled advertising contexts by confirming that perceived usefulness remains the dominant determinant of purchase intention. Despite the increasing sophistication of AI technologies, consumers continue to prioritize functional value and decision-support capability over technological novelty, reinforcing the enduring explanatory power of TAM in AI-mediated marketing environments [42].

Third, the study refines digital trust theory by clarifying that trust functions primarily as a facilitating cognitive condition rather than an independent behavioral driver. Although personalization significantly enhances perceived trust, trust alone does not translate directly into purchase intention after accounting for perceived relevance and perceived usefulness. This finding suggests that trust reduces consumers' uncertainty, whereas the perceived functional value of AI-generated recommendations ultimately drives purchasing decisions.

Finally, by integrating TPB, TAM, digital trust theory, and the Stimulus–Organism–Response framework, this study provides a more comprehensive explanation of how AI-driven personalization influences consumer behavior through sequential cognitive mechanisms. In doing so, it contributes to the growing body of AI marketing literature by clarifying the psychological processes linking algorithmic personalization with purchase intention.

5.3. Managerial implications

The findings suggest that e-commerce platforms should prioritize the functional value generated by AI personalization rather than increasing algorithmic complexity alone. Since perceived usefulness represents the strongest determinant of purchase intention, AI-powered recommendation systems should focus on delivering relevant information, reducing consumers' search effort, and improving decision efficiency throughout the purchasing process.

In addition, organizations should strengthen consumer trust by implementing transparent data governance, explainable AI recommendations, and consistent personalization practices. Although trust does not directly influence purchase intention, it remains an essential foundation for encouraging consumers to accept and engage with AI-generated recommendations within digital commerce environments.

5.4. Limitations and future research

This study has several limitations that provide opportunities for future research. First, the reliance on cross-sectional, self-reported data collected from Shopee users in Vietnam limits causal inference and the generalizability of the findings across different cultural and platform contexts. Future studies should adopt longitudinal or experimental designs and conduct cross-national comparisons to validate the proposed framework.

Second, the present model focuses primarily on cognitive mechanisms. Future research may extend this framework by incorporating affective factors, privacy concerns [64], [65], generative AI ethics, and broader post-purchase outcomes, including customer loyalty and electronic word-of-mouth (eWOM) [66], to develop a more comprehensive understanding of AI-enabled consumer behavior.

5.5. Final Positioning Statement

The findings suggest that the effectiveness of AI-driven personalization depends less on algorithmic sophistication than on its ability to enhance consumers' perceptions of usefulness, contextual relevance, and decision efficiency. Accordingly, AI creates strategic value not through personalization alone, but through enabling more informed and cognitively efficient purchase decisions.

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