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AI-Driven Personalization and Consumer Trust in Digital Retail Service Systems

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Abstract. This study examines how artificial intelligence (AI)–driven personalization influences consumer trust and behavioral intention in digital retail service systems. Drawing on the Stimulus–Organism–Response (S–O–R) framework and trust theory, AI-driven personalization is conceptualized as a service stimulus that shapes consumer trust, which in turn drives behavioral responses such as purchase intention, repeat-purchase intention, and recommendation intention. Beyond consumer-facing recommendations, the study situates AI-driven personalization within platform-based retail service operations, where it interacts with order fulfillment, platform coordination, delivery reliability, inventory visibility, and customer-service workflows to shape the overall service experience. Survey data were collected from 320 active online shoppers of major Vietnamese e-commerce platforms, Shopee, Lazada, Tiki, and TikTok Shop, between February and April 2025 using an online questionnaire distributed through a consumer panel. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were used as the primary estimation approach, with ordinary least squares (OLS) regression employed as a robustness check. The results indicate that AI-driven personalization has a significant positive effect on consumer trust, suggesting that relevant and tailored recommendations enhance consumers' perceptions of platform reliability and competence. Consumer trust, in turn, exerts a strong positive influence on behavioral intention. A bias-corrected bootstrap test (5,000 resamples) confirms that consumer trust fully mediates the relationship between AI-driven personalization and behavioral intention. The study extends the S–O–R framework to AI-driven digital retail service systems and provides a parsimonious model that highlights the central role of trust. Managerial implications emphasize the importance of designing effective personalization strategies while ensuring transparency and responsible data practices to sustain consumer trust and engagement.

Keywords: AI-driven personalization; digital retail service systems; consumer trust; behavioral intention; S–O–R framework; service informatics

1. Introduction

Artificial intelligence has reshaped how digital retailers design and deliver services. E-commerce platforms now routinely use AI to analyze consumer data, anticipate preferences, and tailor product recommendations, advertisements, search results, and promotional messages to individual shoppers (Raji et al., 2024; Sipos, 2025). Beyond marketing, AI-driven personalization has become a core informatics capability that shapes multiple service dimensions of the digital retail platform, including search efficiency, customer journey design, service responsiveness, product discovery, and overall platform service quality (Tam & Ho, 2006; Bleier & Eisenbeiss, 2015; Hassan et al., 2025). Recommendation engines reduce search costs by filtering large product catalogs; predictive analytics support journey design by anticipating the next-best action; conversational agents and adaptive search interfaces improve service responsiveness; and personalized content increases the relevance of product discovery. In this sense, AI-driven personalization is no longer a peripheral marketing feature but a service-level informatics capability that defines the modern digital retail experience (Nguyen et al., 2025).

Importantly, in a digital retail service system, personalization is not confined to the consumer-facing storefront; it is embedded in, and dependent upon, the platform's underlying service operations. Recommendation engines and predictive targeting draw on the same data infrastructure that supports order fulfillment, platform coordination, delivery reliability, inventory visibility, and customer-service workflows. Personalized recommendations are only credible when they are coordinated with real-time inventory and reliable fulfillment, and personalized post-purchase communication depends on responsive customer-service processes. Framing AI-driven personalization as a service-operations capability, rather than a standalone marketing function, aligns the present study with research on digital retail service systems and platform-based service operations (Nguyen et al., 2025; De et al., 2023), and clarifies why personalization shapes not only what consumers see but how they evaluate the reliability of the service as a whole.

The value of this shift becomes clearer when one considers the information overload that characterizes contemporary online retail. A typical e-commerce platform offers far more products, brands, price points, and reviews than any individual consumer can reasonably evaluate, and this abundance often stalls rather than supports decision-making (Pappas, 2018). Personalized recommendation systems counter this friction by narrowing the choice set to items the shopper is more likely to want. Empirical evidence has consistently linked AI-powered personalization to stronger engagement, satisfaction, loyalty, and purchase intention, primarily through gains in recommendation relevance and decision-making efficiency (Komiak & Benbasat, 2006; Li et al., 2023; Hassan et al., 2025).

Yet the same mechanism that makes personalization useful also places consumer trust at risk. Delivering tailored experiences requires the collection, processing, and interpretation of substantial volumes of user data; consumers who perceive such practices as intrusive, opaque, or overreaching often respond with concerns about privacy, data security, and algorithmic fairness (Awad & Krishnan, 2006; Chen et al., 2022). Prior research indicates that the trust and loyalty benefits of personalization can be substantially offset when privacy concerns or perceptions of intrusiveness rise (Song et al., 2021; Jayapal, 2025). The way in which AI-driven personalization, consumer trust, and behavioral outcomes interact therefore remains an open empirical question in service informatics research.

This study investigates that interaction within digital retail service systems. The Stimulus–Organism–Response (S–O–R) framework (Mehrabian & Russell, 1974) provides a natural theoretical lens: AI-driven personalization serves as the external service stimulus, consumer trust represents the internal psychological state, and behavioral intention captures the resulting response. S–O–R fits the present problem because it explicitly accounts for the way that service features are internally evaluated before they translate into behavioral choices. Three research questions guide the study:

Research Question 1: How does AI-driven personalization influence consumer trust in digital retail service systems?
Research Question 2: How does consumer trust affect behavioral intention in digital retail service systems?
Research Question 3: Does consumer trust mediate the relationship between AI-driven personalization and behavioral intention?

The study makes three contributions. First, it reframes AI-driven personalization as an informatics-enabled service capability rather than a marketing tactic. Viewed in this way, personalization is not only about pushing products; it is a broader digital service function that combines consumer data, algorithms, and platform intelligence to enhance search efficiency, journey design, and service responsiveness. Second, by pairing the S–O–R framework with trust theory, the study articulates the psychological pathway linking personalization to behavior. Treating trust as the organism-level response to AI-enabled stimuli clarifies why personalization influences behavioral intention, not just that it does, a distinction that helps connect technical service design to behavioral outcomes. Comparable evidence in the Vietnamese service economy shows that perceived service quality mediates the link between service innovation and customers' behavioral responses (Ho et al., 2025). Third, the study offers a parsimonious model built around the mediating role of trust. Keeping the model compact preserves the core mechanism without introducing additional constructs that may confound interpretation. The findings provide digital retailers with practical guidance on how to advance personalization without eroding the trust that makes it effective.

2. Literature Review

2.1. AI-Driven Personalization in Digital Retail Service Systems

Research on digital retail service systems increasingly treats AI-driven personalization as an information-systems capability embedded in platform service operations rather than as an isolated marketing tactic (Nguyen et al., 2025). From this perspective, personalization is one component of a broader service architecture that also encompasses search and discovery, recommendation, fulfillment coordination, and customer support. Recent information-systems scholarship situates AI within e-commerce alongside recommender systems, demand forecasting, inventory optimization, and fraud detection, underscoring that personalization both draws on and feeds back into the operational layer of the platform (Nguyen et al., 2025).

Two streams of the information-systems and service literature are especially relevant. The first is the privacy-calculus and personalization–privacy paradox literature, which holds that consumers weigh the benefits of personalization against the perceived costs of disclosing personal data; trust is sustained only when perceived benefits outweigh privacy costs (Awad & Krishnan, 2006; Chen et al., 2022). The second is the emerging literature on algorithmic transparency and explainable AI, which argues that consumers’ willingness to rely on AI-generated recommendations depends on the perceived intelligibility and accountability of the underlying algorithms (Nguyen et al., 2025). Although the present study does not measure privacy concern, transparency, or explainability directly, these literatures frame the boundary conditions within which personalization builds, or erodes, consumer trust, and they motivate the cautious interpretation adopted in the discussion.

2.2. AI-Driven Personalization and Consumer Trust

AI-driven personalization refers to the use of artificial intelligence, machine-learning algorithms, and consumer data to tailor digital retail services to individual users (Tam & Ho, 2006; Raji et al., 2024). On e-commerce platforms, this tailoring takes many forms, including product recommendations, targeted advertisements, customized search results, dynamic pricing suggestions, and individualized promotional content. Each of these capabilities enables the platform to respond more precisely to user preferences, thereby raising the perceived usefulness of the service (Komiak & Benbasat, 2006; Sipos, 2025).

Within the S–O–R framework, personalization operates as the service stimulus. It shapes the digital shopping environment by influencing what consumers see, how they evaluate products, and how efficiently they reach a purchase decision. When personalized recommendations effectively match consumer preferences, shoppers tend to perceive the platform as competent, responsive, and attentive to their needs. Prior research supports this interpretation: AI-based personalization has been shown to enhance trust and satisfaction by aligning recommendations with consumers' preferences and purchase goals (Bleier & Eisenbeiss, 2015; Hassan et al., 2025).

Trust theory adds a further layer to the argument. Online shopping is inherently uncertain because consumers cannot physically inspect products or interact with sellers before committing to a transaction (McKnight et al., 2002; Gefen et al., 2003). Consumers therefore rely on platform-provided signals, including product information, recommendation systems, peer reviews, and the transaction process itself. Accurate and useful personalization functions as one of these trust signals: when the platform consistently surfaces relevant options, consumers infer that the platform understands them, and that inference translates into greater confidence in their purchase decisions (Komiak & Benbasat, 2006; Pavlou, 2003).

The trust-building effect of personalization is, however, conditional on consumers' assessment of the platform's data practices. Personalization perceived as excessive or intrusive can produce discomfort, suspicion, and a decline in trust. Research on privacy concerns, opaque data handling, and perceived surveillance consistently demonstrates that such perceptions can erode the benefits that personalization would otherwise generate (Awad & Krishnan, 2006; Chen et al., 2022; Song et al., 2021). In other words, personalization strengthens trust only when consumers perceive it as relevant, useful, and handled responsibly. This reasoning leads to the following hypothesis:

H1: AI-driven personalization positively influences consumer trust in digital retail service systems.

2.3. Consumer Trust and Behavioral Intention

Consumer trust is a central psychological mechanism in digital retail service systems. It reflects consumers' confidence that a platform is reliable, secure, and capable of delivering expected service outcomes (McKnight et al., 2002; Gefen et al., 2003). In online shopping, trust is particularly important because consumers face risks related to product quality, payment security, delivery reliability, and data privacy. When consumers trust a platform, they are more likely to engage with its services and rely on its recommendations (Pavlou, 2003; ElSayad & Mamdouh, 2024).

Within the S–O–R framework, consumer trust represents the internal organism state that links digital service stimuli to behavioral responses. AI-driven personalization can attract attention and improve the shopping experience, but consumers are more likely to convert these experiences into behavioral intention when they trust the platform. Trust reduces perceived risk and increases willingness to complete transactions (Pavlou & Fygenson, 2006; De et al., 2023). Prior studies show that trust plays an important role in shaping purchase intention, loyalty, and continued platform usage in AI-enabled retail environments (Hassan et al., 2025; Sipos, 2025).

Behavioral intention in digital retail service systems encompasses both short-term and longer-term self-reported behavioral responses, including purchase intention, repeat-purchase intention, and recommendation intention (Zeithaml et al., 1996; Pavlou & Fygenson, 2006). In the short term, trust increases consumers' willingness to purchase recommended products. In the longer term, trust supports repeat purchasing and word-of-mouth recommendation. Studies on AI-powered recommendation systems confirm that trust is closely associated with stronger purchase intention, customer satisfaction, and recommendation intention (Gallin & Portes, 2024; Hassan et al., 2025). Related evidence from e-commerce settings further links service-delivery performance to customer loyalty (Lubis et al., 2025).

Therefore, consumer trust is expected to function as a key driver of behavioral intention. When consumers believe that a digital retail platform is trustworthy, they are more likely to accept personalized recommendations, complete purchases, and return to the platform. Trust is thus not only a psychological outcome of AI-driven personalization but also a behavioral driver supporting digital retail performance. Based on this reasoning, the following hypothesis is proposed:

H2: Consumer trust positively influences behavioral intention in digital retail service systems.

2.4. The Mediating Role of Consumer Trust

The S–O–R framework explicitly positions the organism state as the mechanism through which external stimuli translate into behavioral responses (Mehrabian & Russell, 1974). In the present context, this implies that the effect of AI-driven personalization on behavioral intention is not purely direct but is conveyed through the development of consumer trust. Personalization on its own may attract attention and signal relevance, but its translation into purchase, repeat-purchase, and recommendation intentions depends on whether consumers come to trust the platform that produces these tailored experiences (Komiak & Benbasat, 2006; Pavlou, 2003).

Empirical evidence consistent with this view shows that trust often absorbs much of the effect of service-quality and personalization stimuli on behavioral outcomes (Gefen et al., 2003; Pavlou & Fygenson, 2006; Hassan et al., 2025). To operationalize the S–O–R logic fully, the conceptual model includes both the indirect path from personalization to behavioral intention through trust and the residual direct path from personalization to behavioral intention; the mediation hypothesis is evaluated by jointly estimating both paths. In line with this reasoning, the following mediation hypothesis is proposed:

H3: Consumer trust mediates the relationship between AI-driven personalization and behavioral intention in digital retail service systems.

3. Methodology and Data Collection

3.1. Data Collection and Sample

Data were collected through a structured online questionnaire targeting consumers in Vietnam who had prior experience with major digital retail platforms employing AI-driven personalization. Vietnam was chosen as the empirical setting because it is one of the most rapidly growing digital retail markets in Southeast Asia, with widespread consumer use of platforms that deploy AI-driven recommendation systems, personalized advertising, and algorithmic search. The target platforms were Shopee, Lazada, Tiki, and TikTok Shop, which together account for the large majority of business-to-consumer e-commerce activity in Vietnam.

The questionnaire was distributed between February and April 2025 through an online consumer panel maintained by a professional market-research provider, supplemented by snowball sampling through social-media channels. A screening question at the beginning of the survey ensured that only respondents who reported active use of at least one of the four target platforms within the preceding six months, and who confirmed prior interaction with personalized features (e.g., personalized product recommendations, algorithmic search results, or targeted promotional content), were retained. Of 612 individuals who started the survey, 358 completed it (completion rate 58.5%); after removing responses that failed attention checks, completed the survey in under three minutes, or exhibited straight-line answer patterns, a final analytical sample of 320 valid responses was retained.

The questionnaire was developed in English, translated into Vietnamese, and then back-translated to ensure equivalence. It comprised three sections. The first collected demographic information, including age, gender, education level, and online shopping frequency (Table 1). The second measured AI-driven personalization and consumer trust. The third measured behavioral intention, including purchase intention, repeat-purchase intention, and recommendation intention. All measurement items were assessed on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 1. Demographic Profile of Respondents (N = 320)

Variable	Category	Frequency	Percentage (%)
Gender	Male	148	46.25
	Female	172	53.75
Age	18–24	96	30.00
	25–34	124	38.75
	35–44	62	19.38
	45 and above	38	11.87
Education	High school or below	58	18.13
	Bachelor's degree	182	56.87
	Master's degree or above	80	25.00
Shopping Frequency	Rarely	42	13.13
	Occasionally	118	36.87
	Frequently	160	50.00

3.2. Measurement of Variables

The three latent constructs, AI-driven personalization (PER), consumer trust (TRUST), and behavioral intention (BI), were measured using multi-item scales adapted from established prior literature. AI-driven personalization items were adapted from Komiak and Benbasat (2006) and Tam and Ho (2006) and capture perceived relevance, tailoring, and decision support delivered by the platform. Consumer trust items were adapted from McKnight, Choudhury, and Kacmar (2002) and Gefen, Karahanna, and Straub (2003) and capture perceived reliability, security, and benevolence of the platform. Behavioral intention items were adapted from Zeithaml, Berry, and Parasuraman (1996) and Pavlou and Fygenson (2006), and cover purchase intention, repeat-purchase intention, and recommendation intention. The complete item wording and corresponding sources are reported in Table 2.

Table 2. Measurement Items and Sources

Construct	Code	Measurement Item	Adapted From
AI-Driven Personalization (PER)	PER1	The platform provides personalized product recommendations.	Komiak & Benbasat (2006); Tam & Ho (2006)
	PER2	Recommendations from the platform match my preferences.	Komiak & Benbasat (2006)
	PER3	The platform appears to understand my needs.	Tam & Ho (2006)
	PER4	Personalized content improves my shopping experience.	Bleier & Eisenbeiss (2015)
Consumer Trust (TRUST)	TRUST1	I trust this platform.	Gefen, Karahanna & Straub (2003)
	TRUST2	The platform is reliable.	McKnight, Choudhury & Kacmar (2002)
	TRUST3	I feel secure when using this platform.	McKnight et al. (2002)
	TRUST4	The platform protects my personal information.	Pavlou (2003)
Behavioral Intention (BI)	BI1	I intend to purchase from this platform.	Pavlou & Fygenson (2006)
	BI2	I am likely to buy products recommended by the platform.	Pavlou & Fygenson (2006)
	BI3	I will continue to purchase from this platform in the future.	Zeithaml, Berry & Parasuraman (1996)

Construct	Code	Measurement Item	Adapted From
	BI4	I would recommend this platform to others.	Zeithaml et al. (1996)

Formally, each latent construct is measured by its set of observed indicators, which are aggregated into a composite score using the mean of the corresponding items. For individual *i*, let PER_i, $TRUST_i$, and BI_i denote AI-driven personalization, consumer trust, and behavioral intention, respectively:

$$PER_i = (1 / K)\ \Sigma_{k=1}^{K} PER_{ik} \tag{1}$$

$$TRUST_i = (1 / M)\ \Sigma_{m=1}^{M} TRUST_{im} \tag{2}$$

$$BI_i = (1 / N)\ \Sigma_{n=1}^{N} BI_{in} \tag{3}$$

where K, M, and N denote the number of items used to measure each construct ($K = M = N = 4$). This aggregation is used only to construct composite scores for the OLS robustness analysis; in the primary SEM analysis, the constructs are modeled as latent variables with their full set of indicators.

3.3. Empirical Model Specification

Following Anderson and Gerbing's (1988) two-step approach, this study first assesses the measurement model and then estimates the structural model. The primary estimation approach is structural equation modeling (SEM) with maximum-likelihood estimation, which permits simultaneous estimation of the relationships among latent constructs while accounting for measurement error. Ordinary least squares (OLS) regression on the composite construct scores is then used as a robustness check.

Measurement-model evaluation follows established procedures in service informatics research. Internal-consistency reliability is assessed using Cronbach's alpha (α) and composite reliability (CR), with values above 0.70 considered acceptable. Convergent validity is examined through standardized factor loadings from confirmatory factor analysis (CFA) and the average variance extracted (AVE), with loadings above 0.70 and AVE above 0.50 indicating adequate convergent validity. Discriminant validity is evaluated using the Fornell–Larcker (1981) criterion: the square root of AVE for each construct is compared with its correlations with the other constructs.

The structural model corresponds to the S–O–R logic and tests H1–H3 simultaneously. For latent constructs, the model is specified as:

$$TRUST_i = \alpha_0 + \alpha_1 \cdot PER_i + \alpha_C \cdot Controls_i + \varepsilon_{1i} \tag{4}$$

$$BI_i = \beta_0 + \beta_1 \cdot TRUST_i + \beta_2 \cdot PER_i + \beta_C \cdot Controls_i + \varepsilon_{2i} \tag{5}$$

where α_1 captures the effect of AI-driven personalization on consumer trust (H1), β_1 captures the effect of consumer trust on behavioral intention (H2), and the indirect effect $\alpha_1 \times \beta_1$ captures the mediating effect of trust (H3). Controls is a vector of control variables comprising age, gender, education, and online shopping frequency. The mediation hypothesis (H3) is tested using a bias-corrected bootstrap procedure with 5,000 resamples (Hayes, 2018); the control variables are included in both the mediator and outcome equations during the mediation estimation, and the indirect effect is considered supported when its 95% bias-corrected confidence interval excludes zero.

4. Results and Discussion

4.1. Measurement Model and Preliminary Analysis

Before estimating the structural relationships, several preliminary checks were performed to confirm that the data were suitable for factor analysis and that the measurement model held up. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were first computed. The KMO value was 0.891, well above the recommended 0.70 threshold, and Bartlett's test was statistically significant ($\chi^2 = 1523.476$, df = 66, $p < 0.001$), confirming that the data were appropriate for factor analysis (Table 3).

Table 3. KMO and Bartlett's Test

Test	Value
Kaiser–Meyer–Olkin (KMO)	0.891
Bartlett's test χ^2	1523.476
df	66
Sig.	0.000

With the data confirmed as factorable, an exploratory factor analysis (EFA) was performed using principal axis factoring (PAF) with promax rotation. PAF was chosen over principal component analysis because it is a latent-variable factor method appropriate when the goal is to estimate common-factor structure rather than to summarize the data. The EFA produced a clean three-factor solution corresponding to PER, TRUST, and BI, with all items loading on their intended construct above 0.70 and no cross-loadings exceeding 0.30. The three factors together accounted for 71.4% of the total variance.

Table 4. EFA Results (Principal Axis Factoring, Promax Rotation)

Construct	Item	PER	TRUST	BI
PER	PER1	0.812		
	PER2	0.846		
	PER3	0.862		
	PER4	0.742		
TRUST	TRUST1		0.889	
	TRUST2		0.873	
	TRUST3		0.768	
	TRUST4		0.821	
BI	BI1			0.872
	BI2			0.841
	BI3			0.735
	BI4			0.801

Notes: Extraction method: principal axis factoring; rotation method: promax. Cross-loadings below 0.30 suppressed.

Confirmatory factor analysis (CFA) was then conducted to evaluate the measurement model. The three-factor CFA produced a good fit to the data: $\chi^2 = 109.83$, df = 51, $\chi^2/df = 2.15$, CFI = 0.962, TLI = 0.951, RMSEA = 0.060, SRMR = 0.039. All standardized loadings exceeded 0.70 and were significant at $p < 0.001$, and all indicator error variances ($1 - \lambda^2$) were significant and below 0.50, indicating that each item is well explained by its latent construct. As reported in Table 5, the composite reliability (CR) of each construct exceeded 0.90, Cronbach's alpha exceeded 0.80, and the average variance extracted (AVE) exceeded 0.50, supporting internal consistency and convergent validity.

Table 5. CFA Results: Reliability and Convergent Validity

Construct	Items	Std. Loadings	Cronbach's α	CR	AVE
PER	4	0.748–0.871	0.892	0.914	0.682
TRUST	4	0.772–0.893	0.906	0.927	0.703
BI	4	0.738–0.876	0.887	0.911	0.674

Discriminant validity was assessed via the Fornell–Larcker criterion. As Table 6 shows, the square root of AVE for each construct (in bold on the diagonal) exceeds its correlation with each of the other constructs, supporting discriminant validity.

Table 6. Discriminant Validity (Fornell–Larcker Criterion)

Construct	PER	TRUST	BI
PER	**0.826**		
TRUST	0.543	**0.838**	
BI	0.488	0.613	**0.821**

Notes: Diagonal entries (in bold) are the square root of AVE; off-diagonal entries are construct correlations.

Common method bias (CMB) was assessed using three procedures. First, Harman's single-factor test indicated that the first factor accounted for 38.42% of the total variance, well below the 50% critical threshold. Second, a single-factor CFA in which all items loaded on a single latent factor produced a substantially worse fit than the three-factor model (single-factor: $\chi^2/df = 6.84$, CFI = 0.711, RMSEA = 0.135), indicating that a single latent factor cannot account for the covariance structure. Third, a full collinearity test based on variance inflation factors (VIF) yielded values between 1.42 and 1.71, all below the 3.30 threshold recommended by Kock (2015). Taken together, these tests suggest that CMB is unlikely to pose a serious threat to the validity of the results.

Table 7. Multicollinearity (Full Collinearity VIF)

Variable	VIF	Tolerance
PER	1.432	0.698
TRUST	1.587	0.630
BI	1.713	0.584

4.2. Descriptive Statistics

Table 8 presents the descriptive statistics for the composite construct scores. The mean of AI-driven personalization (PER) is 3.783, indicating that respondents generally perceive personalized features as moderately high on the digital retail platforms studied. Consumer trust (TRUST) has a mean of 3.654, suggesting a relatively positive level of confidence in platform reliability. Behavioral intention (BI) has a mean of 3.720, reflecting a strong tendency toward self-reported purchase, repeat-purchase, and recommendation intentions. The standard deviations range from 0.682 to 0.742, indicating moderate variation across respondents. Because each construct is measured as the mean of multiple Likert items, the composite variables are treated as continuous.

Table 8. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
PER	320	3.783	0.712	1.632	4.958
TRUST	320	3.654	0.682	1.587	4.921
BI	320	3.720	0.742	1.603	4.973

Table 9 reports the Pearson correlation matrix. AI-driven personalization is positively correlated with consumer trust ($r = 0.543$, $p < 0.001$) and with behavioral intention ($r = 0.488$, $p < 0.001$), and consumer trust is strongly correlated with behavioral intention ($r = 0.613$, $p < 0.001$). All bivariate correlations are below 0.80, indicating no multicollinearity concerns.

Table 9. Correlation Matrix

Variable	PER	TRUST	BI
PER	1.000		
TRUST	0.543***	1.000	
BI	0.488***	0.613***	1.000

*Notes: *** p < 0.001.*

4.3. Structural Model: Hypothesis Testing

The structural model was estimated using SEM with maximum-likelihood estimation. Model fit was acceptable: $\chi^2/df = 2.13$, CFI = 0.957, TLI = 0.948, RMSEA = 0.059, SRMR = 0.041 (Table 11). As reported in Table 10, AI-driven personalization has a significant positive effect on consumer trust ($\beta = 0.523$, $p < 0.001$), supporting H1. Consumer trust, in turn, exerts a strong positive effect on behavioral intention ($\beta = 0.641$, $p < 0.001$), supporting H2. The residual direct path from personalization to behavioral intention is not significant ($\beta = 0.072$, $p = 0.142$). The structural model includes all four control variables (age, gender, education, shopping frequency), and explains 35.1% of the variance in consumer trust ($R^2 = 0.351$) and 42.4% of the variance in behavioral intention ($R^2 = 0.424$).

Table 10. Structural Model Results (SEM, Primary Estimation)

Path	Std. β	Std. Error	t-value	p-value	Hypothesis
PER → TRUST	0.523	0.046	11.370	0.000	H1: supported
TRUST → BI	0.641	0.050	12.820	0.000	H2: supported
PER → BI (direct)	0.072	0.049	1.469	0.142	-

Notes: Controls (age, gender, education, shopping frequency) included; full estimates available on request.

The mediating role of consumer trust (H3) was tested using a bias-corrected bootstrap procedure with 5,000 resamples (Table 12). The indirect effect of AI-driven personalization on behavioral intention through consumer trust is positive and significant ($\beta = 0.328$, 95% CI [0.253, 0.404], $p < 0.001$), while the direct effect of personalization on behavioral intention is not significant ($\beta = 0.072$, $p = 0.142$). Because the indirect effect is significant while the direct effect is not, the result is consistent with full mediation. H3 is therefore supported: consumer trust mediates the relationship between AI-driven personalization and behavioral intention.

Table 11. SEM Model-Fit Indices

Fit Index	Value	Threshold	Result
χ^2/df	2.134	< 3	Good
CFI	0.957	> 0.90	Good
TLI	0.948	> 0.90	Good
RMSEA	0.059	< 0.08	Good
SRMR	0.041	< 0.08	Good

Table 12. Mediation Analysis (Bias-Corrected Bootstrap, 5,000 Resamples)

Path	Effect	Std. Error	t-value	p-value	95% CI LL	95% CI UL
PER → TRUST	0.519	0.048	10.813	0.000	0.425	0.612
TRUST → BI	0.632	0.052	12.154	0.000	0.531	0.733
PER → BI (direct)	0.072	0.049	1.469	0.142	-0.025	0.169
PER → TRUST → BI (indirect)	0.328	0.039	8.410	0.000	0.253	0.404

4.4. Robustness Check: OLS Regression

As a robustness check, the relationships were re-estimated using OLS regression on the composite construct scores, controlling for age, gender, education, and online shopping frequency (Table 13). Consistent with the SEM results, AI-driven personalization has a significant positive effect on consumer trust ($\beta = 0.519$, $p < 0.001$), and consumer trust has a significant positive effect on behavioral intention ($\beta = 0.632$, $p < 0.001$). Among the control variables, online shopping frequency is positive and significant in both models, indicating that more experienced online shoppers tend to exhibit higher trust and behavioral intention. Age, gender, and education are not statistically significant. The OLS estimates are consistent in sign and magnitude with the SEM estimates, supporting the robustness of the findings.

Table 13. OLS Regression Results (Robustness Check)

Variable	Model 1: TRUST	Model 2: BI
PER	0.519*** (0.000)	-
TRUST	-	0.632*** (0.000)
Age	-0.032 (0.287)	-0.019 (0.413)
Gender	0.042 (0.198)	0.036 (0.222)
Education	0.018 (0.471)	0.024 (0.398)
Shopping frequency	0.142** (0.004)	0.129* (0.024)
Constant	1.782*** (0.000)	1.564*** (0.000)
R^2	0.347	0.416
Adjusted R^2	0.337	0.405
F-statistic	32.18***	41.74***
Observations	320	320

*Notes: p-values are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.*

4.5. Discussion

The empirical results provide strong support for the proposed S–O–R framework. AI-driven personalization meaningfully strengthens consumer trust, and consumer trust, in turn, translates into stronger behavioral intention. The positive relationship between personalization and trust confirms that well-designed personalization operates as an effective service stimulus: when shoppers find recommendations relevant and useful, they tend to perceive the platform itself as competent and dependable. This finding is consistent with prior work showing that AI-powered personalization enhances trust and satisfaction (Bleier & Eisenbeiss, 2015; Sipos, 2025; Hassan et al., 2025).

These findings should, however, be read alongside the broader privacy literature. Several prior studies demonstrate that the trust-building effect of personalization depends on how consumers interpret the platform's data practices and the transparency of its algorithms (Awad & Krishnan, 2006; Chen et al., 2022; Song et al., 2021). Because privacy concern, perceived intrusiveness, and algorithmic transparency are not measured in the present study, these constructs are not part of the empirical model; they are discussed in the literature review as theoretical boundary conditions and are addressed explicitly as future-research directions in the conclusion.

The second link, from trust to behavioral intention, was equally clear in the data, confirming that trust is a core mechanism behind self-reported behavioral responses in digital retail. This is consistent with earlier work showing that trust reduces perceived risk and increases willingness to transact online (Gefen et al., 2003; Pavlou & Fygenson, 2006; ElSayad & Mamdouh, 2024). In AI-driven retail specifically, trust carries additional weight because consumers rely on algorithmic recommendations rather than direct product inspection. Gallin and Portes (2024) extend this point by showing that trust and perceived system performance jointly shape both deliberate purchases and impulse buying.

The mediation result (H3) carries the strongest substantive implication. Because the indirect effect of personalization on behavioral intention through trust is significant while the direct effect is not, the data are consistent with a full-mediation interpretation: AI-driven personalization affects self-reported purchase-related behavioral intention primarily through its impact on consumer trust. This finding confirms the central organism role of trust within the S–O–R framework and indicates that personalization without trust is unlikely to translate into stronger behavioral intentions.

These consumer-perception findings also have implications for the service-operations layer of digital retail platforms. Because trust is the mechanism through which personalization influences behavioral intention, the operational processes that underpin trust, reliable order fulfillment, accurate inventory visibility, coordinated delivery, and responsive customer-service workflows, are not peripheral to personalization but complementary to it. Personalized recommendations that are not backed by dependable fulfillment and service operations risk undermining the very trust they are intended to build. This interpretation links the present consumer-level results to the broader digital retail service-systems literature (Nguyen et al., 2025; De et al., 2023) and suggests that personalization strategy and service-operations design should be managed jointly rather than separately.

The study contributes to the literature in several ways. First, it extends S–O–R to AI-driven digital retail service systems by empirically showing that personalization acts as the stimulus and trust as the mediating organism state. Second, it integrates trust theory with personalization research, establishing trust as both an outcome of AI-enabled services and a driver of the behavioral intentions that follow. Third, by working with a deliberately parsimonious model, the study isolates the core mechanism without diluting it through additional constructs.

For managers, the implications are practical. Digital retailers should treat AI-driven personalization as a genuine investment priority because the gains in trust and behavioral intention are substantial. This implies sustained investment in recommendation algorithms that are accurate, relevant, and useful. At the same time, transparency in data practices is essential: consumers need to understand how personalization works and how their data are handled. Because perceived intrusiveness can undermine the very trust that personalization builds, managers should balance personalization intensity with meaningful user control over data and personalization settings. The basics also matter: a reliable, secure, and consistent platform is what converts short-term engagement into long-term customer relationships.

5. Conclusion

This study examined how AI-driven personalization shapes consumer trust and self-reported behavioral intention in digital retail service systems. Drawing on the Stimulus–Organism–Response (S–O–R) framework, AI-driven personalization was treated as a service stimulus that acts on consumer trust, which in turn shapes behavioral intention. The empirical results support all three hypotheses: AI-driven personalization significantly enhances consumer trust (H1); consumer trust significantly enhances behavioral intention (H2); and consumer trust fully mediates the relationship between personalization and behavioral intention (H3).

The findings indicate that when shoppers perceive recommendations as relevant, useful, and aligned with their preferences, they are more inclined to regard the platform as reliable and competent, a pattern consistent with previous work on personalization as a driver of customer experience and trust in digital settings (Komiak & Benbasat, 2006; Hassan et al., 2025). Importantly, the mediation result clarifies the mechanism: positive perceptions of personalization translate into stronger behavioral intentions only when they generate consumer trust.

The study contributes to the literature in several distinct ways. It extends the S–O–R framework into AI-enabled digital retail service systems by providing empirical evidence that personalization functions as a service stimulus mediated by trust. It connects trust theory with personalization research by showing that trust is both a product of AI-driven services and a driver of downstream behavioral intention. And by working with a parsimonious model, it offers a focused account of how personalization influences behavior without introducing additional variables that could obscure the underlying mechanism.

Practical implications follow directly. Digital retailers should treat effective personalization, and the recommendation algorithms that drive it, as a priority investment, because these are the levers that shape consumer perceptions. Managers should also pay attention to the flip side: personalization that feels excessive or intrusive can erode the very trust it was meant to build, especially when consumers suspect that their data are not being handled transparently (Awad & Krishnan, 2006; Chen et al., 2022).

Transparent data practices, clear explanations of how personalization operates, and meaningful user control over data settings are therefore essential. Getting the balance right between personalization and privacy is what sustains consumer trust over the long run.

Several limitations should be noted. First, the study relies on self-reported survey responses rather than transaction logs; the dependent variable should be interpreted as self-reported purchase-related behavioral intention rather than observed purchase behavior. Second, the cross-sectional research design constrains causal inference; longitudinal or experimental designs would be better suited to capturing how perceptions and behaviors evolve over time. Third, the data were collected from users of four major Vietnamese e-commerce platforms, so generalization to other countries, platform categories, or regulatory environments should be made with care. Fourth, although the literature review draws on the privacy-calculus, transparency, and service-operations literatures, several relevant constructs are not measured in the present model. Future research should incorporate privacy concern, perceived intrusiveness, algorithmic transparency, explainable AI, satisfaction, perceived usefulness, and algorithmic fairness, as well as service-operations constructs such as delivery reliability, order-fulfillment quality, and inventory visibility, to test whether they moderate or mediate the personalization-trust-intention relationship. Cross-cultural and regulatory comparisons, as well as studies of emerging technologies such as explainable AI and augmented reality, also represent promising avenues for future work.

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