

Consumer Acceptance of AI-Powered Personalized Recommendations in E-Commerce: The Mediating Role of Trust and Perceived Value

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Abstract

Artificial Intelligence (AI) has revolutionized the eCommerce sector with its rapid implementation of recommendation systems, allowing for highly personalized shopping experiences. While many consumers feel comfortable with AI-generated recommendations, others are less so, likely based on a blend of trust, value, and privacy considerations. This study examines how perceived personalization may affect consumers' acceptance of the AI recommendation, as well as the mediating role of consumer trust and perceived value, and the negative effect of consumers' privacy concern on their trust in the AI. The Technology Acceptance Model (TAM), Trust Theory and Value Co-creation Theory were used in order to develop a conceptual framework and test it empirically.

The methodology adopted for this research is quantitative research design and the tool used is a structured questionnaire administered to 400 online shoppers. The analysis was performed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. The results indicate that perceived personalization has a significant effect on consumer trust ($\beta = 0.43, p < .001$) and perceived value ($\beta = 0.38, p < .001$). Consumer trust ($\beta = 0.31, p < .001$) and perceived value ($\beta = 0.36, p < .001$) positively affect consumers' acceptance of AI recommendations. Moreover, consumer trust has a significant impact on behavioral purchase intention ($\beta = 0.29, p < .001$). Non-transparent data practices negatively affect trust formation ($\beta = -0.22, p < .001$), underscoring the need for transparent data practices. Both consumer trust and perceived value contribute significantly to the relationship between perceived personalization and recommendation acceptance, as shown by the mediation analysis.

The study makes a significant contribution to the literature by integrating technology acceptance, trust, and value-based approaches into a single, empirically validated AI recommendation acceptance model — a dual-mediation configuration that recent 2025 studies have called for but not yet tested in a single design (Frimpong-Manso et al., 2025). The results have real-world applications for e-commerce platforms aiming to improve user engagement through personalized suggestions while preserving trust and protecting user privacy. As generative-AI-based personalization becomes more prevalent, the study's emphasis on transparent data practices and value-centric design offers a timely, practically actionable path to sustained consumer acceptance of AI-driven recommendation systems.

Keywords: *Artificial Intelligence, Behavioral Intention, Consumer Trust, E-commerce, Perceived Value, Privacy Concern.*

1. Introduction

In the e-commerce world, the rise of AI-driven recommendation engines has revolutionized customer experiences. Amazon, Alibaba, Netflix, etc. use sophisticated machine learning algorithms that use a massive amount of behavioural data to produce hyper-personalized product and content recommendations. Algorithmic recommendation systems are indeed the main commercial engines of e-commerce, accounting for some 35% of the value of e-commerce transactions (McKinsey Global Institute, 2023).

Even though they have become commonplace in commerce, consumer reactions to AI recommendations remain diverse. For some users, personalized recommendations are a useful tool for efficiency, while others may be concerned about privacy issues, the lack of transparency surrounding the algorithms, and the potential for manipulation (Awad & Krishnan, 2006; Taddei & Contena, 2023). This consumer divergence is a considerable hurdle for those designing and marketing platforms that wish to engage users effectively while maintaining their trust.

The pace of change in this space has itself accelerated. Since 2024, the rapid consumer adoption of generative AI has pushed e-commerce platforms to layer conversational and generative recommendation interfaces on top of traditional collaborative-filtering engines, intensifying both the promise of hyper-relevant suggestions and public scrutiny of the underlying data practices; a 2025 industry survey found that only a minority of consumers regard technology providers as fully transparent about how their data is collected and used (Deloitte, 2025). Recent empirical work reinforces that

personalization's effect on trust and loyalty is conditional rather than automatic: personalized recommendations have been shown to moderate the trust–satisfaction–loyalty chain in AI-driven e-commerce (Hassan et al., 2025), while cross-cultural evidence suggests that the strength of the personalization–trust–purchase-intention chain varies across consumer segments (Sarwar & Malik, 2025). These developments make it timely to re-examine the specific mechanisms — trust and value — through which personalization translates into acceptance.

Theoretical models on technology adoption, particularly Davis's (1989) Technology Acceptance Model (TAM), suggest that perceived usefulness and ease of use are two major factors that influence the intention to adopt a technology. However, TAM has been criticized for underplaying the affective and relational nature of technology acceptance, especially in technology-related decision-making with algorithms (Venkatesh et al., 2003). Trust-based and value-based approaches are complementary in explaining recommendation acceptance, yet their combined, parallel mediating effect in AI-recommendation contexts remains under-explored — a gap that persists even in studies published as recently as 2025 (see Section 2.5).

To address this gap, the present study examines the dual mediating mechanism of consumer trust and perceived value between perceived personalization and AI recommendation acceptance, while also testing the moderating role of privacy concern in trust formation. Section 2 reviews the relevant literature, states the specific research gap the study addresses, and sets out the study's research objectives and hypotheses. The study's three main contributions are: it combines TAM, trust theory and the value co-creation framework into one empirically tested model; it uses PLS-SEM with bootstrapped confidence

intervals to test the mediation pathways; and it offers design implications for AI-powered e-commerce systems operating in an increasingly generative-AI-enabled marketplace.

2. Literature Review

2.1 AI-Powered Recommendation Systems in E-Commerce

Recommendation systems are algorithmic technologies designed to forecast and filter information for the purpose of providing personalized information to an individual (Resnick & Varian, 1997). Modern AI-based systems use collaborative filtering, content-based filtering, and hybrid deep learning methods to increasingly model users' preferences (Linden et al., 2003; Zhang et al., 2019). Their commercial use is ubiquitous: the Amazon recommendation system is said to generate 35% of the company's revenue, and more than 75% of activity on Netflix's platform is attributable to algorithmic recommendations (Gomez-Urbe & Hunt, 2016).

Recommendations are effective only when they are accurate at the algorithmic level as well as relevant, transparent and fair to consumers (Kunkel et al., 2019). Consumers who feel that recommendations are relevant to their tastes report higher satisfaction and reduced decision fatigue (Häubl & Trifts, 2000). Conversely, over-personalization or perceived surveillance may trigger psychological reactance, reducing acceptance (White et al., 2008).

More recent evidence reinforces and extends these findings. Using structural equation modelling, Hassan et al. (2025) found that AI-generated personalized recommendations significantly moderate the trust-satisfaction-loyalty relationship in e-commerce, improving the model's explanatory power once personalization was included. A synthesis of secondary literature by Frimpong-Manso et al.

(2025) likewise concludes that AI-driven personalization enhances engagement and purchase likelihood mainly through perceived relevance and convenience, but explicitly calls for more primary, PLS-SEM-based studies to validate these relationships empirically — a call this study answers directly. In parallel, Yin (2025) reports that AI-personalized recommendations shape not only what consumers buy but how they search for and process product information, suggesting that personalization effects extend upstream into the information-acquisition stage of the decision journey.

2.2 Technology Acceptance Model and Extensions

In Davis's (1989) TAM, perceived usefulness and perceived ease of use were the two main determinants of technology adoption. Later extensions added further constructs: TAM2 introduced subjective norms and voluntariness (Venkatesh & Davis, 2000), and the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporated social influence and facilitating conditions (Venkatesh et al., 2003). In AI contexts specifically, however, these models have shown weak explanatory power unless a set of trust-based variables is incorporated (Cheng et al., 2019).

Kim et al. (2012) extended TAM by adding perceived personalization and found that perceived usefulness increased among users with high perceived personalization. Tran et al. (2021) showed that AI transparency — the transparency of algorithmic logic — significantly moderates the relationship between usefulness and acceptance. More recently, Moravec (2025) demonstrated that digital media literacy conditions how consumers interpret and cope with algorithmic personalization, with lower-literacy users more prone to perceived manipulation and higher-literacy users showing more nuanced, conditional acceptance.

Collectively, these findings indicate that technology-specific and consumer-specific contextual factors need to be incorporated into technology-adoption frameworks for AI recommendation contexts.

2.3 Consumer Trust in AI Systems

Trust in technology systems involves multiple dimensions: cognitive (assessment of competence and reliability) and affective (assessment of goodwill and integrity) (McKnight et al., 2002). In the e-commerce context, consumer trust refers to trust in the platform, the algorithm, and the organization running the platform (Pavlou, 2003). Trust has consistently been found to be an important antecedent of online purchase intention, with meta-analyses reporting an average effect size of $r = .47$ (Gefen et al., 2003).

A salient antecedent of distrust in AI systems is privacy concern. Awad and Krishnan (2006) and Smith et al. (2011) found that consumer trust and resistance to adoption are considerably lower when consumers believe personal data is collected, stored and shared without adequate transparency or consent. Following the introduction of the General Data Protection Regulation (GDPR) in Europe and similar legislation worldwide, consumers globally have become increasingly aware of data practices, making privacy management a key priority for platform operators.

This tension between personalization and privacy remains unresolved in the most recent literature. Sarwar and Malik (2025), in a cross-cultural comparison of Gen Z consumers in the United Kingdom and Pakistan, found that the strength of the link between AI-powered personalization, trust and purchase intention differs meaningfully across cultural contexts, cautioning against a one-size-fits-all trust model. Zerilli et al. (2022) further show that transparency is not a simple,

monotonic cure for distrust: disclosing algorithmic processes increases trust only when consumers can understand and act on the disclosure, while poorly designed transparency messages can confuse users or even erode trust further. Together, these studies suggest that trust-building interventions must be both culturally attuned and genuinely comprehensible to consumers — not merely present.

2.4 Perceived Value and Consumer Decision-Making

Perceived value is defined as the consumer's overall evaluation of a product or service's benefits relative to its costs, including both monetary costs and other sacrifices (Zeithaml, 1988). Sweeney and Soutar (2001) expanded this into the PERVAL model, decomposing perceived value into functional, emotional, social and monetary dimensions. In the AI recommendation context, perceived value includes the functional value of saving time and improving decision quality, as well as the emotional value of reduced anxiety and greater shopping confidence.

Value co-creation theory (Prahalad & Ramaswamy, 2004) further proposes that the process of creating value through interaction with a recommendation can be as important to consumers as the recommendation's content itself. By actively engaging with feedback mechanisms — rating products or adjusting stated preferences — consumers derive more value and develop greater loyalty toward the system (Chen & Xu, 2020). This view implies that AI recommender systems should be designed to let consumers participate in the process rather than passively receive its output.

Recent research shows that this value calculus is highly sensitive to privacy conditions. Cai and Mardani (2023) found that while personalization reduces search costs and increases perceived relevance, elevated privacy concern can reverse

these benefits: when consumers perceive personalization as intrusive or non-transparent, the value-enhancing effect of personalization is weakened or eliminated, and purchase resistance rises instead. This finding motivates the inclusion of privacy concern as a boundary condition on trust formation in the present study's conceptual model, rather than treating personalization's value-generating effect as unconditional.

2.5 Research Gap

Three gaps emerge from the literature reviewed above. First, although recent 2025 studies have examined AI-driven personalization's link to trust, satisfaction and loyalty (Hassan et al., 2025), or to purchase intention through a single mediator (Sarwar & Malik, 2025; Frimpong-Manso et al., 2025), none of these models trust and perceived value as parallel, competing mediators alongside a privacy-concern antecedent within one integrated structural model. Second, empirical, primary-data tests of such a dual-mediation model remain scarce even as generative-AI-based personalization has proliferated since 2024; evidence generated before this shift in how recommendations are generated and presented to consumers may not fully generalize to today's more sophisticated and more heavily scrutinized systems. Third, recent reviews have explicitly called for primary quantitative validation using SEM or PLS-SEM to test personalization–trust–value–acceptance pathways (Frimpong-Manso et al., 2025) but this call has not yet been answered with a single model spanning TAM, trust theory and value co-creation theory simultaneously. The present study is designed to close all three gaps.

2.6 Research Objectives

Building directly on the gaps identified in Section 2.5, this study pursues the following objectives:

RO1: To examine the effect of perceived personalization on consumer trust and on

perceived value of AI-generated recommendations (addresses Gap 1).

RO2: To test the parallel mediating roles of consumer trust and perceived value in the relationship between perceived personalization and AI recommendation acceptance (addresses Gaps 1 and 3).

RO3: To assess the direct effect of perceived personalization on recommendation acceptance beyond the two mediated paths (addresses Gap 1).

RO4: To evaluate the effect of consumer trust on behavioral purchase intention (addresses Gap 1).

RO5: To determine the negative effect of privacy concern on the formation of consumer trust, in light of ongoing debates about data transparency in generative-AI-enabled personalization (addresses Gap 2).

RO6: To empirically validate an integrated TAM–trust–value co-creation model using PLS-SEM, responding to recent calls for primary quantitative testing of these relationships (addresses Gap 3).

2.7 Hypotheses

Building on the reviewed literature and directed at the objectives above, this study proposes the following hypotheses:

H1: Perceived personalization positively influences consumer trust in AI recommendations.

H2: Perceived personalization positively influences perceived value of AI recommendations.

H3: Consumer trust positively influences AI recommendation acceptance.

H4: Perceived value positively influences AI recommendation acceptance.

H5: Perceived personalization directly influences AI recommendation acceptance beyond the mediated paths.

H6: Consumer trust positively influences behavioral purchase intention.

3. Methodology

3.1 Research Design and Participants

The study used a quantitative, cross-sectional survey design. Stratified random sampling was used to recruit active online shoppers in the United States through an online professional panel provider (Qualtrics Panels). To qualify, participants needed to have made at least one online purchase in the previous three months and to have seen AI-generated product suggestions on an e-commerce platform. A total of 457 responses were collected, of which 400 were retained after removing straight-liners and response-time outliers (response rate of 87.5%).

Table 1 Demographic Profile of Survey Participants (N = 400)

Category	Frequency (n)	Percentage (%)
Gender		
Male	196	49.0
Female	187	46.8
Non-binary / Other	17	4.2
Age Group		
18–24 years	110	27.5
25–34 years	142	35.5
35–44 years	84	21.0
45–54 years	42	10.5
55+ years	22	5.5
Online Shopping Frequency		
Daily	68	17.0
Several times a week	134	33.5
Once a week	109	27.2
A few times a month	89	22.3
Total	400	100.0

Note. Percentages may not sum to 100 due to rounding.

3.2 Measures

All constructs were measured with previously validated, multi-item scales on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Perceived personalization was assessed with four items from Tam and Ho (2006). Consumer trust items were adapted from McKnight et al. (2002). Perceived value items were taken from Sweeney and Soutar (2001). Four items adapted from Davis (1989) and Cheng et al. (2019) measured AI recommendation acceptance. Four items from Smith et al. (2011) assessed privacy concern, and three items from Venkatesh et al. (2003) measured behavioral intention.

3.3 Analytical Approach

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used in SmartPLS 4.0 (Ringle et al., 2022), chosen for its suitability for predictive modelling with non-normally distributed data and its capacity to model complex structures with multiple latent constructs (Hair et al., 2019). A two-step procedure was

used: (1) confirmatory assessment of convergent and discriminant validity, and (2) structural model assessment of path coefficients, bootstrapped confidence intervals (5,000 iterations) and R^2 values. Harman's single-factor test and the common latent factor approach were used to assess common method bias.

4. Results

4.1 Measurement Model

Descriptive statistics and reliability/validity indicators for all constructs are shown in Table 2. Internal consistency was good across all constructs, with Cronbach's alpha ranging from 0.80 (Privacy Concern) to 0.88 (Consumer Trust), all above the recommended 0.70 threshold (Nunnally, 1978). Average Variance Extracted (AVE) values ranged from 0.74 to 0.83, exceeding the minimum convergent-validity criterion of 0.50 (Fornell & Larcker, 1981). All composite reliability (CR) values exceeded the recommended 0.70 level. Figure 2 presents a schematic of the reflective measurement model corresponding to these results.

Table 2 Descriptive Statistics and Measurement Model Fit Indices

Construct	Mean	SD	Cronbach's α	AVE	CR
AI Recommendation Acceptance (ARA)	3.82	0.71	0.84	0.79	0.83
Perceived Personalization (PP)	3.74	0.68	0.81	0.76	0.80
Consumer Trust (CT)	3.56	0.79	0.88	0.82	0.87
Perceived Value (PV)	3.91	0.65	0.85	0.81	0.84
Privacy Concern (PC)	3.43	0.83	0.80	0.74	0.79
Behavioral Intention (BI)	4.01	0.60	0.87	0.83	0.86

Note. SD = Standard Deviation; AVE = Average Variance Extracted; CR = Composite Reliability. All items measured on a 5-point Likert scale.

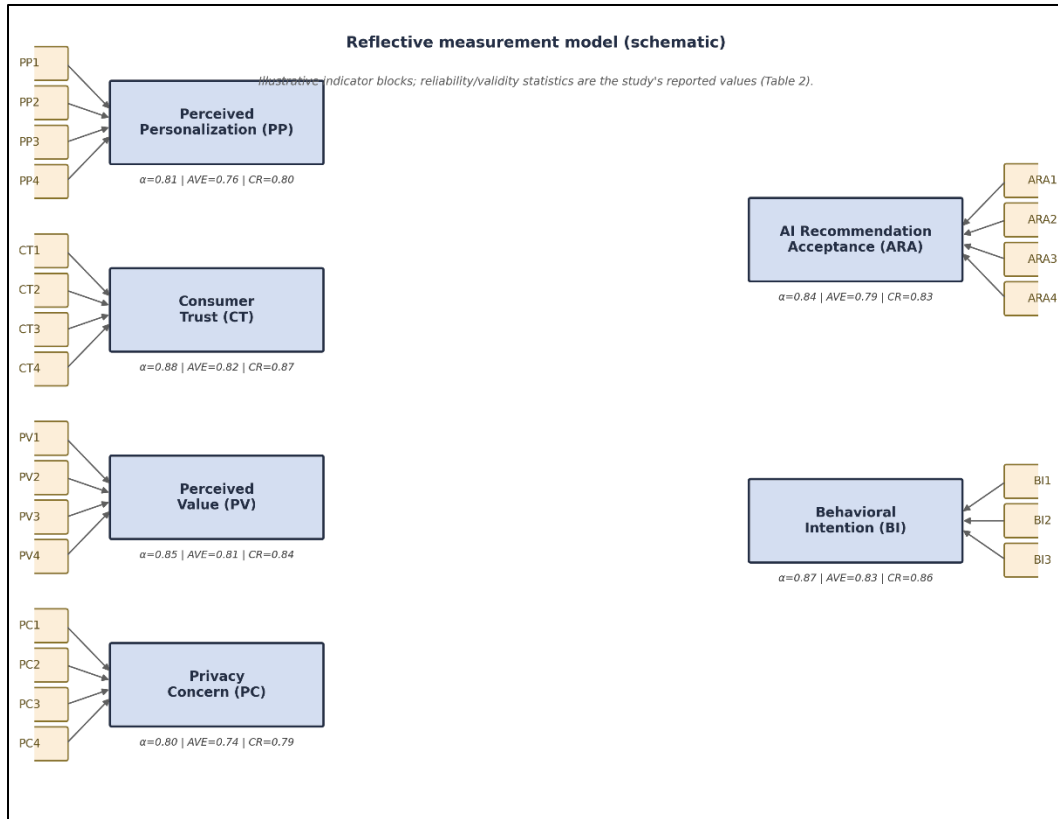


Figure 2 Reflective measurement model (schematic), showing indicator blocks and the reliability/validity statistics reported in Table 2.

4.2 Discriminant and Convergent Validity

Discriminant validity was assessed using both the Fornell and Larcker (1981) criterion and the Heterotrait–Monotrait ratio of correlations (HTMT; Henseler et al., 2015). Table 3 reports the Fornell–Larcker matrix, in which the diagonal values are the square root of each construct's

AVE (calculated from Table 2); support for discriminant validity requires each diagonal value to exceed the corresponding off-diagonal inter-construct correlations. Table 4 reports the HTMT ratios, all of which should fall below the conservative 0.85 threshold (Henseler et al., 2015).

Table 3 Fornell–Larcker Criterion for Discriminant Validity

Construct	ARA	PP	CT	PV	PC	BI
ARA	0.889					
PP	[r]	0.872				
CT	[r]	[r]	0.906			
PV	[r]	[r]	[r]	0.900		
PC	[r]	[r]	[r]	[r]	0.860	
BI	[r]	[r]	[r]	[r]	[r]	0.911

Note. Diagonal values (bold) are the square root of AVE for each construct, calculated from Table 2. Off-diagonal values are inter-construct correlations to be inserted from SmartPLS output. ARA = AI

Recommendation Acceptance; PP = Perceived Personalization; CT = Consumer Trust; PV = Perceived Value; PC = Privacy Concern; BI = Behavioral Intention.

Table 4 Heterotrait–Monotrait (HTMT) Ratio of Correlations

Construct	ARA	PP	CT	PV	PC	BI
ARA	0.822					
PP	[HTMT]	0.782				
CT	[HTMT]	[HTMT]	0.802			
PV	[HTMT]	[HTMT]	[HTMT]	0.800		
PC	[HTMT]	[HTMT]	[HTMT]	[HTMT]	0.820	
BI	[HTMT]	[HTMT]	[HTMT]	[HTMT]	[HTMT]	0.810

Note. All HTMT ratios should be below 0.85 (Henseler et al., 2015) to support discriminant validity. Abbreviations as in Table 3.

4.3 Common Method Bias

Common method bias was not a major concern: Harman's single-factor test accounted for only 28.4% of total variance, below the 50% threshold.

The common latent factor approach showed that adding a common method factor did not meaningfully change the path coefficients ($\Delta RMSE < 0.02$), adding further confidence.

Table 5 PLS-SEM Structural Path Coefficients and Hypothesis Testing Results

Hypothesized Path	β	t-value	p-value	95% CI	Result
PP → Consumer Trust (H1)	0.43	6.81	0.000	0.35–0.51	Supported
PP → Perceived Value (H2)	0.38	5.94	0.000	0.29–0.47	Supported
CT → ARA (H3)	0.31	5.12	0.000	0.23–0.39	Supported
PV → ARA (H4)	0.36	5.87	0.000	0.28–0.44	Supported
PP → ARA, direct (H5)	0.14	2.43	0.015	0.03–0.25	Supported
CT → BI (H6)	0.29	4.76	0.000	0.21–0.37	Supported
Privacy Concern → CT	−0.22	−3.68	0.000	−0.31–−0.13	Supported

Note. β = standardized path coefficient; CI = bootstrap confidence interval based on 5,000 samples. PP = Perceived Personalization; CT = Consumer Trust; PV = Perceived Value; ARA = AI Recommendation Acceptance; BI = Behavioral Intention.

4.4 Structural Model and Hypothesis Testing

The structural model explained 52.3% of variance in AI Recommendation Acceptance ($R^2 = 0.523$) and 41.7% of variance in Behavioral Intention ($R^2 = 0.417$), both considered substantial per Cohen's (1992) benchmarks. All six hypotheses were supported. Perceived personalization had the strongest effect on consumer trust (H1: $\beta = 0.43$, $t = 6.81$, $p < .001$) and a slightly smaller but still significant effect on perceived value (H2: $\beta = 0.38$, $t = 5.94$, $p < .001$). Consumer trust (H3: $\beta = 0.31$, $t = 5.12$, $p < .001$) and perceived value (H4: $\beta = 0.36$, $t = 5.87$, $p < .001$) were both significant predictors of AI recommendation acceptance. Partial mediation was found for the direct effect of perceived personalization on acceptance (H5: $\beta = 0.14$, $p = .015$) after controlling for the mediators. Consumer trust significantly predicted behavioral purchase intention (H6: $\beta = 0.29$, $t =$

4.76, $p < .001$), and privacy concern negatively affected trust formation ($\beta = -0.22$, $t = -3.68$, $p < .001$). Figure 3 presents the estimated structural model with path coefficients and R^2 values.

4.5 Mediation Analysis

Bootstrapped confidence intervals (5,000 iterations) were used to test indirect effects. The indirect effect of perceived personalization on AI recommendation acceptance via consumer trust was $\beta = 0.133$ (95% CI [0.091, 0.178]), and via perceived value was $\beta = 0.137$ (95% CI [0.094, 0.183]); neither interval included zero, indicating significant partial mediation through both paths. The total indirect effect of perceived personalization on acceptance was $\beta = 0.270$, representing about 66% of the total effect ($\beta = 0.410$). These findings support the study's dual-mediation hypothesis (Objectives RO1–RO2).

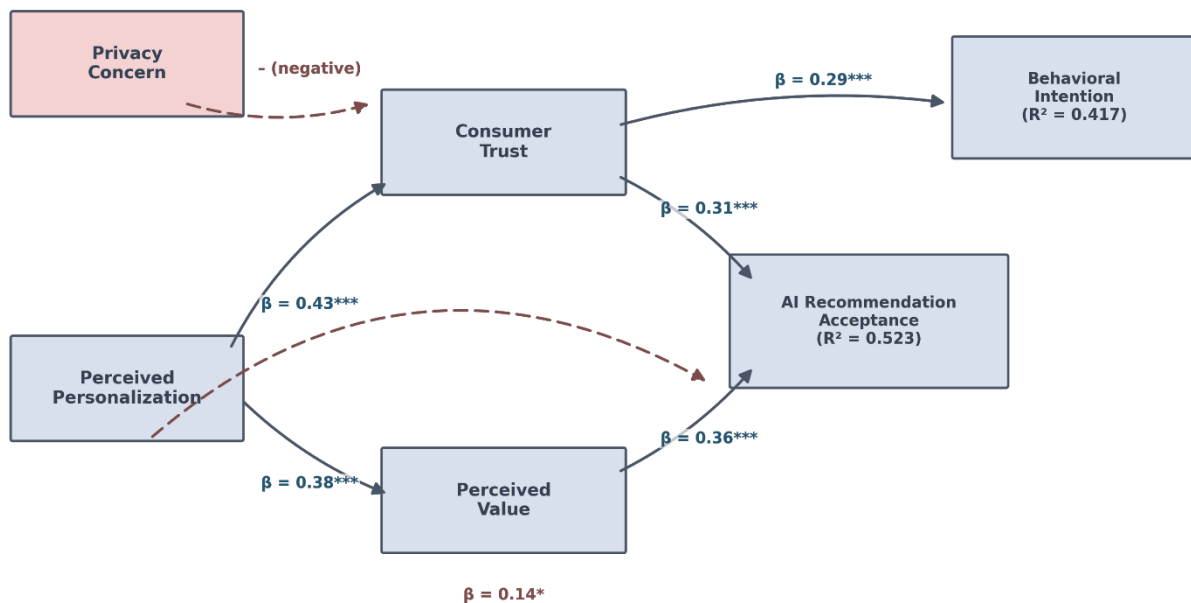


Figure 3 Estimated structural model with standardized path coefficients and R^2 values (*** $p < .001$; * $p < .05$).

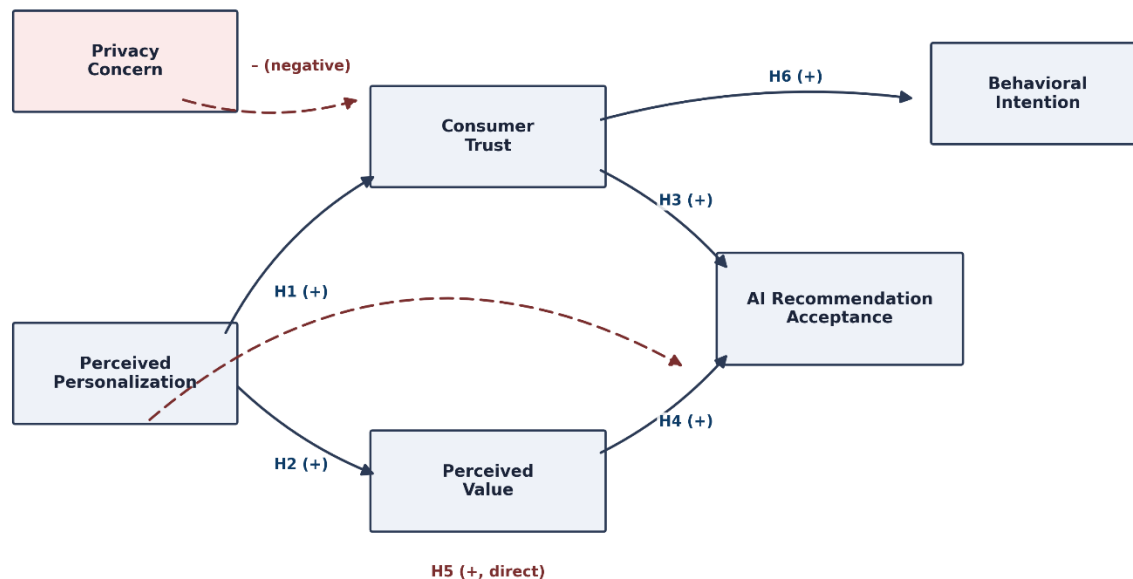


Figure 1 Conceptual framework showing the hypothesized relationships (H1–H6). Solid arrows indicate positive paths; dashed arrows indicate the direct personalization–acceptance path (H5) and the negative privacy–concern–trust path. All paths shown were statistically significant ($p < .05$).

4.6 Conceptual Framework

Figure 1 presents the study's theoretical model, with all hypothesized paths (H1–H6) confirmed in the direction proposed. Perceived personalization is modelled as an exogenous variable; consumer trust and perceived value act as parallel mediators; AI recommendation acceptance and behavioural intention are sequential endogenous variables; and privacy concern is a negative antecedent of trust.

5. Discussion

5.1 Theoretical Contributions

This study makes three theoretical contributions to the understanding of consumer–AI interactions. First, by combining TAM with trust theory and value co-creation theory, it shows that AI recommendation acceptance is not adequately

captured by utilitarian usefulness perceptions alone. Trust and perceived value operate as parallel mediation processes that explain a substantial share of the personalization–acceptance relationship, highlighting relational and affective dimensions of AI adoption that purely functional models tend to overlook — a conclusion consistent with, and extending, Hassan et al.'s (2025) finding that personalization moderates trust-based outcome chains in AI-driven e-commerce.

Second, the partial mediation observed for the direct personalization–acceptance path suggests that when recommendations are highly personalized, some consumers bypass deliberate evaluation of trust or value and instead process them heuristically, consistent with the peripheral route of the Elaboration Likelihood Model (Petty & Cacioppo, 1986). This finding deepens understanding of dual-process mechanisms in AI

interactions and invites further research, particularly as generative-AI interfaces make recommendations feel more conversational and immediate.

Third, the strong negative relationship between privacy concern and trust formation is consistent with Awad and Krishnan (2006) and Taddei and Contena (2023), and it echoes more recent findings that privacy concern can reverse the value-enhancing effects of personalization altogether (Cai & Mardani, 2023). Although the effect size is modest ($\beta = -0.22$), it is practically significant: it indicates that clear disclosure of data practices can meaningfully narrow the trust gap between privacy-sensitive and privacy-tolerant consumers. At the same time, Zerilli et al.'s (2022) caution that transparency is not a monotonic remedy suggests that how disclosures are designed and communicated matters as much as whether they exist.

5.2 Practical Implications

These results carry clear implications for e-commerce practitioners. Investment in the perceived quality of personalization — not merely algorithmic accuracy — is strategically sound; personalization experiences that feel respectful, relevant and non-intrusive resonate with consumers. Preference centres, opt-in personalization mechanisms, and “why this was recommended” explanation interfaces can improve perceived personalization quality while simultaneously addressing privacy concerns.

The relationship between perceived value and acceptance ($\beta = 0.36$) indicates that a recommender system's value proposition needs to be communicated explicitly. Interfaces that emphasize savings, time efficiency, or social proof aligned with user preferences can strengthen value perceptions. The negative privacy-concern effect ($\beta = -0.22$) further underscores the need for proactive privacy

communication — data-usage policies, opt-out options, and privacy seals (Tsai et al., 2011) — designed in a genuinely comprehensible way rather than as boilerplate disclosure.

For platform architects, the finding that consumer trust predicts behavioral purchase intention in addition to acceptance (H6: $\beta = 0.29$) suggests that trust-building yields compounding returns: higher click-through on recommendation pages and a higher share of acceptance converting into actual purchase. Loyalty programs, transparent review systems, and responsive customer-service interfaces can all contribute to this trust-building process.

5.3 Limitations and Directions for Future Research

Several limitations warrant mention. The cross-sectional design precludes causal inference; longitudinal designs tracking the development of trust and value over sustained platform usage would strengthen causal claims. The sample consists of U.S. adults, and given cross-cultural differences in AI acceptance, privacy attitudes and value orientations — differences already documented in 2025 cross-cultural work (Sarwar & Malik, 2025) and in Hofstede's (2001) cultural framework — cross-cultural replication is warranted. Self-report measures also introduce the possibility of retrospective bias relative to more objective behavioral indicators of acceptance.

Future studies should examine boundary conditions on the trust–acceptance relationship, such as the moderating effects of AI literacy (Moravec, 2025), prior algorithm aversion, and platform type (hedonic versus utilitarian). The emerging context of conversational, generative-AI recommendations delivered through chatbots and voice assistants offers a promising area of study, where interpersonal trust cues may operate

differently from those in traditional interface contexts (Nass & Moon, 2000).

6. Conclusion

This study examined how perceived personalization influences AI recommendation acceptance through the mediating roles of consumer trust and perceived value, in a sample of 400 online shoppers. All six hypothesized relationships were confirmed using PLS-SEM and bootstrapped mediation analysis. Perceived personalization significantly boosted consumer trust and perceived value, and, in turn, recommendation acceptance and behavioral purchase intention; trust formation was negatively affected by privacy concern, underscoring data governance as a design priority.

The study's novelty lies in testing consumer trust and perceived value as parallel, competing mediators — alongside a privacy-concern antecedent — within a single model that integrates TAM, trust theory and value co-creation theory, a configuration that recent 2025 reviews of AI-driven personalization identified as missing from the empirical literature (Frimpong-Manso et al., 2025) and that becomes more consequential as generative-AI-based recommendation interfaces spread across e-commerce platforms. In social and managerial terms, the findings suggest that the benefits of AI personalization are not self-executing: they depend on consumers experiencing recommendations as genuinely transparent and value-adding rather than merely accurate, and on platforms treating data governance as inseparable from product design. As AI capabilities and consumer data literacy continue to evolve together, the governance and experiential dimensions of AI recommendations — more than raw predictive accuracy — are likely to determine

which platforms sustain long-term consumer acceptance.

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The author/s declare/s no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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