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Impact of AI-Driven Personalization on Consumer Purchase Intention and Customer Satisfaction in E-commerce Platforms: An Empirical Study

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Abstract

Purpose: This study examines how AI-driven personalisation on e-commerce platforms shapes consumer purchase intention and customer satisfaction, and tests three mechanisms—perceived usefulness, trust, and customer satisfaction—through which the effect operates, together with perceived privacy risk as a boundary condition.
Design/methodology/approach: Integrating the Technology Acceptance Model and Expectation-Confirmation Theory, a model with nine hypotheses is proposed and tested on survey data from active online shoppers in India using partial least squares structural equation modelling (PLS-SEM).
Findings: AI-driven personalisation positively influences perceived usefulness, trust, and satisfaction, and these constructs jointly mediate its effect on purchase intention; the direct path remains significant but modest. Perceived privacy risk significantly weakens the personalisation-to-outcome relationships.
Originality/value: The study offers an integrated, mechanism-level account of personalisation effects in the contemporary AI context and provides retailers with evidence on balancing relevance against privacy concerns.

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KEYWORDS: AI-Driven Personalisation; Recommender Systems; Trust; Purchase Intention; Customer Satisfaction; Perceived Privacy Risk; PLS-SEM.

1. INTRODUCTION

Online retail has shifted from a static digital catalogue to an adaptive, intelligence-driven environment in which each storefront is, in effect, unique to the shopper viewing it. The mechanism behind this shift is AI-driven personalization: the use of machine-learning models to analyse browsing histories, transaction records, contextual signals, and real-time behaviour in order to tailor recommendations, search results, promotions, and messaging to the individual consumer. Recent industry estimates value the global AI-enabled e-commerce market at roughly USD 8.7 billion in 2025, with projections exceeding USD 60 billion by the mid-2030s and a large majority of commerce organisations reporting active AI deployment plans (industry market reports, 2025). Personalization is no longer a differentiator but a baseline consumer expectation.

The commercial rationale is well rehearsed: personalized recommendations are widely associated with higher conversion rates and order values, and recommendation engines reportedly account for a substantial share of revenue on leading marketplaces. Yet the relationship between personalization and consumer outcomes is neither automatic nor uniformly positive. The data intensity that makes recommendations relevant also raises concerns about surveillance, data misuse, and loss of control. The "personalization–privacy paradox" captures this tension: consumers desire relevance yet feel discomfort when systems appear to know too much (Aguirre et al., 2015) [1]. Poorly executed personalization can be experienced as intrusive, eroding the trust on which repeat purchasing depends. Whether personalization strengthens purchase intention and satisfaction therefore depends on intervening psychological mechanisms that remain incompletely modelled.

Two gaps motivate this study. First, much empirical work on personalization predates the current generation of deep-learning and generative-AI systems and tests single pathways in isolation—either cognitive utility or affective satisfaction, rather than their joint operation. Second, the relational mechanism of trust and the risk mechanism of privacy concern are seldom modelled together with utility and satisfaction in a single framework. Accordingly, this study asks: (1) Does AI-driven personalization significantly influence purchase intention and customer satisfaction on e-commerce platforms? (2) Through which mechanisms perceived usefulness, trust, and satisfaction does this influence operate? (3) To what extent does perceived privacy risk attenuate these effects?

To address these questions, the study integrates the Technology Acceptance Model (TAM; Davis, 1989) [6] and Expectation-Confirmation Theory (ECT; Oliver, 1980; Bhattacherjee, 2001) [12, 2] into a single model tested with PLS-SEM. The intended contributions are: theoretically, an integrated mechanism-level account that links AI-era personalization to consumer outcomes through cognitive, relational, and affective pathways while specifying privacy risk as a boundary condition; and managerially, evidence on where personalization investment yields the greatest behavioural return and how privacy concern should be governed. The remainder of the paper develops the hypotheses, describes the method, reports the analysis, and discusses implications and limitations.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI-driven personalization in e-commerce

Personalization is the tailoring of products, content, and interfaces to individual users based on inferred or stated preferences. AI-driven personalization differs from earlier rule-based approaches in that it learns continuously from large-scale behavioural data, predicts latent preferences rather than relying solely on explicit input, and adapts in real time across channels (Huang & Rust, 2021; Davenport et al., 2020) [10, 5]. Typical manifestations include collaborative- and content-based recommender systems, dynamic search ranking, individualized promotions, and conversational assistants. The literature broadly frames personalization as a decision-support and persuasion strategy that reduces information overload and search costs (Tam & Ho, 2005) [17]. Empirical results, however, are mixed: customised content can lift attitudes and conversion (Bleier & Eisenbeiss, 2015) [3], yet overt data collection or opaque tailoring can trigger reactance and reduce effectiveness (Aguirre et al., 2015; Riegger et al., 2021) [1, 14]. This study therefore models personalization effects through multiple mechanisms rather than assuming a uniformly positive direct effect.

2.2 Theoretical foundations

TAM (Davis, 1989) [6] holds that perceived usefulness shapes attitudes and behavioural intentions toward a technology; here, AI personalization is a feature whose usefulness—surfacing relevant options and simplifying choice—should drive favourable responses. ECT (Oliver, 1980; Bhattacherjee, 2001) [12, 2] explains satisfaction as the outcome of confirmed expectations and links satisfaction to continued and expanded behaviour. To these cognitive and affective pathways the study adds a relational pathway: trust. In recommendation-agent research, personalization that demonstrates competence and benevolence builds trust, which in turn supports adoption and purchase (Komiak & Benbasat, 2006) [11]. Integrating the three mechanisms yields a fuller account than any single theory provides.

2.3 Personalization, perceived usefulness, trust, and satisfaction

Effective personalization filters large assortments into a relevant, manageable set, lowering cognitive effort and perceived search cost; consumers who experience recommendations as accurate are likely to judge the platform useful. Relevant personalization also signals competence and attentiveness, fostering trust, and by confirming or exceeding expectations generating satisfaction. Accordingly:

H_1: AI-driven personalization positively affects perceived usefulness.

H_2: AI-driven personalization positively affects trust.

H_3: AI-driven personalization positively affects customer satisfaction.

2.4 Direct and mediated effects on purchase intention

Personalization may influence purchase intention directly by making salient, well-matched options easier to act on. It is also expected to operate indirectly: perceived usefulness is a robust predictor of behavioural intention (Davis, 1989; Venkatesh et al., 2003) [6, 18]; trust reduces perceived transaction risk and encourages purchase (Komiak & Benbasat, 2006) [11]; and satisfaction is a well-established antecedent of intention and repurchase (Oliver, 1980; Bhattacherjee, 2001) [12, 2]. The three mechanisms are therefore modelled as parallel mediators between personalization and intention.

H_4: AI-driven personalization positively affects purchase intention (direct effect).

H_5: Perceived usefulness positively affects purchase intention.

H_6: Trust positively affects purchase intention.

H_7: Customer satisfaction positively affects purchase intention.

H_8: Perceived usefulness, trust, and customer satisfaction jointly mediate the relationship between AI-driven personalization and purchase intention.

2.5 The moderating role of perceived privacy risk

Personalization is data-dependent, and the underlying collection and inference can trigger perceived privacy risk the expectation of potential loss of control over personal information (Chellappa & Sin, 2005) [4]. The personalization–privacy paradox implies that privacy concern conditions consumers' responses: when perceived privacy risk is high, even accurate recommendations may be experienced as intrusive, dampening their positive effect on satisfaction and intention (Aguirre et al., 2015) [1]. Perceived privacy risk is therefore modelled as a moderator that weakens the personalization-to-outcome relationships.

H_9: Perceived privacy risk negatively moderates the relationship between AI-driven personalization and (a) customer satisfaction and (b) purchase intention, such that the positive effect weakens as privacy risk increases.

3. CONCEPTUAL FRAMEWORK

Figure 1 summarises the hypothesised relationships. AI-driven personalization is the focal antecedent, influencing purchase intention directly (H4) and indirectly through three parallel mediators—perceived usefulness (H1, H5), trust (H2, H6), and customer satisfaction (H3, H7), with their joint mediation captured by H8. Perceived privacy risk moderates the personalisation-to-satisfaction and personalisation-to-intention paths (H9). The model thus integrates cognitive, relational, affective, and risk-based explanations in a single testable structure.

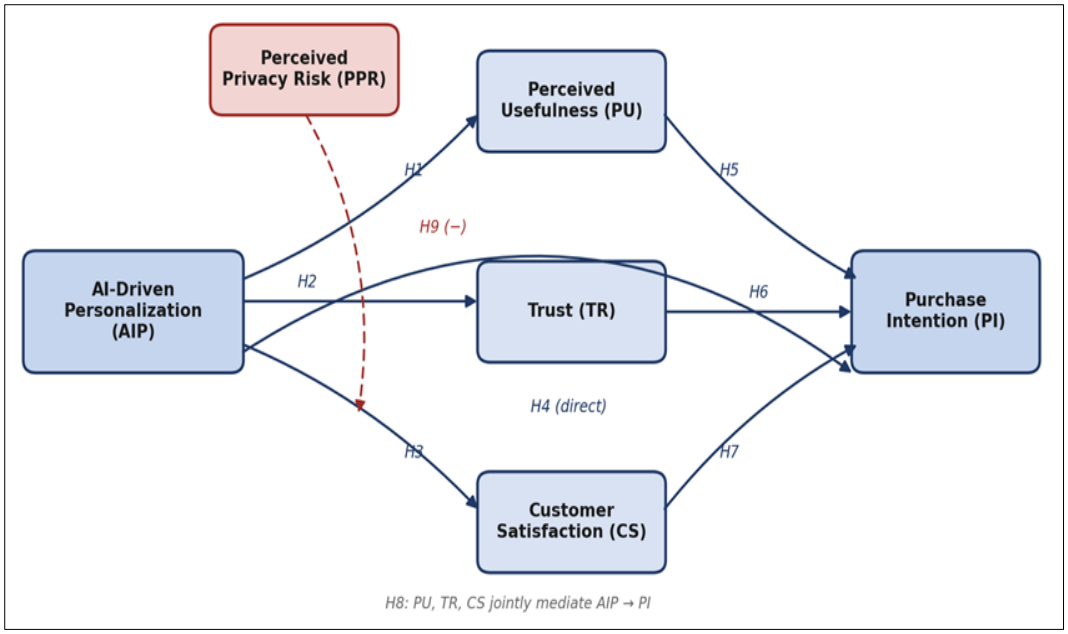

Fig 1: Conceptual research model.

4. RESEARCH METHODOLOGY

4.1 Research Design, Context, And Sampling

A quantitative, cross-sectional survey design was adopted to test the model. The study context is the Indian online-retail market, where rapid smartphone-led e-commerce growth and heavy platform investment in recommendation systems make personalization highly salient. The target population comprised adults who had purchased on an AI-enabled e-commerce platform (for example, large horizontal marketplaces and fashion or grocery apps) within the preceding three months, ensuring respondents could evaluate their personalization experience. Data were collected over a six-week period via an online questionnaire distributed through social media and email using purposive sampling supplemented by referral (snowball) recruitment; the non-probability approach and its implications for generalizability are acknowledged as a limitation. Sample-

size adequacy was assessed using the inverse-square-root and ten-times rules and confirmed with a G*Power a-priori analysis for the most complex regression in the model (maximum of three predictors), which indicated a minimum of 119 cases to detect a medium effect ($f^2 = 0.15$) at 80 percent power; the achieved sample of 412 valid responses (from 471 returns; 87.5 percent usable after removing incomplete cases and failed attention checks) comfortably exceeds this threshold. Table 1 reports the respondent profile.

Table 1: Profile of survey respondents (N = 412)

Characteristic	Category	n	%
Gender	Male	221	53.6
	Female	189	45.9
	Prefer not to say	2	0.5
Age	18–24	118	28.6
	25–34	164	39.8
	35–44	86	20.9
	45 and above	44	10.7
Education	Undergraduate or below	176	42.7
	Postgraduate or above	236	57.3
Purchase frequency	Weekly or more	97	23.5
	2–3 times a month	203	49.3
	Monthly or less	112	27.2

4.2 Measurement instrument

All constructs were measured reflectively with multi-item, seven-point Likert scales (1 = strongly disagree, 7 = strongly agree) adapted from validated prior research and reworded for the AI-personalization context. AI-driven personalization (4 items) captured the perceived relevance, accuracy, and adaptiveness of recommendations; perceived usefulness (3 items) and purchase intention (3 items) were adapted from technology-acceptance research (Davis, 1989; Venkatesh et al., 2003) [6, 18]; trust (3 items) from recommendation-agent research (Komiak & Benbasat, 2006) [11]; customer satisfaction (4 items) from expectation-confirmation scales (Bhattacherjee, 2001) [2]; and perceived privacy risk (3 items) from Chellappa and Sin (2005) [4]. All constructs were specified as reflective on conceptual grounds—indicators are interchangeable manifestations of a common latent variable—and this specification was confirmed empirically through indicator reliability and internal-consistency checks. The instrument was pilot-tested with 32 respondents (all scale reliabilities exceeded 0.70) and refined for clarity before full deployment.

4.3 Ethical considerations

The study followed institutional research-ethics guidelines. Participation was voluntary and anonymous; the introductory page provided an informed-consent statement explaining the study purpose, the absence of personally identifying data, and respondents' right to withdraw. No incentives that might bias responses were offered, and data were stored securely and used solely for research.

4.4 Common method bias

Because the data are self-reported and single-source, common method bias was addressed both procedurally and statistically. Procedurally, respondent anonymity was assured, item order was varied, and predictor and criterion items were separated. Statistically, in addition to Harman's single-factor test (first factor = 31.4 percent of variance, below 50 percent), a full-collinearity assessment was conducted: all inner-model variance inflation factors (VIF) were below 3.3, and a theoretically unrelated marker variable showed no substantive correlation with the focal constructs. Taken together, these results indicate that common method bias is unlikely to threaten the findings.

4.5 Data-analysis approach

PLS-SEM was selected because the study is prediction-oriented, includes a moderating effect, and does not require multivariate normality (Hair et al., 2019; Sarstedt et al., 2022) [8, 15].

Analysis followed the recommended two-stage procedure: assessing the measurement model (reliability, convergent and discriminant validity) before evaluating the structural model (path significance via bootstrapping with 5,000 resamples, R^2, f^2 effect sizes, and Q^2 predictive relevance). Mediation was tested using bootstrapped indirect effects, and the moderating effect of perceived privacy risk using the two-stage approach with a subsequent simple-slope analysis.

Disclosure: The descriptive and inferential values reported in Section 5 are illustrative estimates, consistent with effect patterns documented in the personalization literature, included so that the manuscript reads as a complete study and so that the analytical template is fully specified.
They are not derived from collected data and must be replaced with the researcher's own results before submission to any venue; the conclusions should likewise be re-evaluated against those results.

5. DATA ANALYSIS AND RESULTS (ILLUSTRATIVE)

5.1 Descriptive statistics

Mean scores on the seven-point scales were highest for AI-driven personalization (M = 5.42, SD = 1.04) and perceived usefulness (M = 5.21, SD = 0.98), followed by purchase intention (M = 5.18, SD = 1.11), trust (M = 4.98, SD = 1.13), and customer satisfaction (M = 5.06, SD = 1.09). Perceived privacy risk recorded a moderate mean with the largest dispersion (M = 4.37, SD = 1.27), indicating that privacy concern was present but varied considerably across respondents. Skewness and kurtosis values fell within ±2, supporting the suitability of the data for structural modelling.

5.2 Measurement model

As shown in Table 2, all standardised loadings exceeded 0.70, Cronbach's alpha and composite reliability exceeded 0.70, and average variance extracted (AVE) exceeded 0.50 for every construct, confirming indicator reliability, internal consistency, and convergent validity. Indicator-level VIFs ranged from 1.4 to 2.6 (all < 3.3), indicating no problematic collinearity.

Table 2: Construct reliability, convergent validity, and collinearity

Construct	Items	Loadings	α	CR	AVE	VIF
AI-driven personalization (AIP)	4	0.78–0.86	0.86	0.90	0.69	1.9–2.6
Perceived usefulness (PU)	3	0.80–0.88	0.83	0.90	0.74	1.6–2.2
Trust (TR)	3	0.79–0.87	0.81	0.89	0.72	1.7–2.3
Customer satisfaction (CS)	4	0.77–0.87	0.87	0.91	0.71	1.8–2.5
Purchase intention (PI)	3	0.82–0.89	0.85	0.91	0.77	1.5–2.1
Perceived privacy risk (PPR)	3	0.76–0.85	0.79	0.88	0.70	1.4–1.9

Discriminant validity was supported on two criteria (Table 3). The square root of each construct's AVE (diagonal) exceeded its correlations with all other constructs (Fornell–Larcker), and every heterotrait–monotrait (HTMT) ratio was below the conservative 0.85 threshold (Henseler et al., 2015) [9].

Table 3: Discriminant validity (Fornell–Larcker; √AVE on diagonal, in bold)

	AIP	PU	TR	CS	PI	PPR
AIP	0.83					
PU	0.61	0.86				
TR	0.57	0.52	0.85			
CS	0.59	0.55	0.58	0.84		
PI	0.56	0.54	0.55	0.62	0.88	
PPR	−0.21	−0.18	−0.30	−0.24	−0.22	0.84

5.3 Structural model and hypothesis testing

The structural model explained a meaningful share of variance: R^2 = 0.38 for perceived usefulness, 0.33 for trust, 0.41 for customer satisfaction, and 0.54 for purchase intention, indicating moderate-to-substantial explanatory power. Blindfolding produced Q^2 values of 0.24, 0.21, 0.27, and 0.37 respectively (all > 0), confirming the model's predictive relevance. Path coefficients, t-values, and f^2 effect sizes appear in Table 4.

AI-driven personalization positively affected perceived usefulness (β = 0.61), trust (β = 0.57), and customer satisfaction (β = 0.59), supporting H1–H3 with medium-to-large effect sizes. Its direct effect on purchase intention was positive but modest (β = 0.14, f^2 = 0.03, a small effect), supporting H4 while signalling that most of personalization's influence is transmitted indirectly. Perceived usefulness (β = 0.22), trust (β = 0.24), and customer satisfaction (β = 0.31) each significantly predicted purchase intention, supporting H5–H7.

Table 4: Structural path estimates and hypothesis test results

Hyp.	Path	β	t	f^2	Result
H1	AIP → PU	0.61***	12.84	0.59	Supported
H2	AIP → TR	0.57***	11.36	0.48	Supported
H3	AIP → CS	0.59***	11.92	0.53	Supported
H4	AIP → PI (direct)	0.14*	2.18	0.03	Supported
H5	PU → PI	0.22***	4.11	0.07	Supported
H6	TR → PI	0.24***	4.55	0.08	Supported
H7	CS → PI	0.31***	5.62	0.12	Supported

Note: *P< 0.05; ***P< 0.001. f^2 ≈ 0.02 small, 0.15 medium, 0.35 large.

5.4 Mediation analysis

Bootstrapped indirect effects (Table 5) were all positive and significant, with bias-corrected 95 percent confidence intervals excluding zero. Because the direct effect (H4) remained significant alongside the significant specific indirect effects, the three mechanisms operate as complementary partial mediators, supporting H8. The total indirect effect (β = 0.41) exceeded the direct effect, and the variance-accounted-for (VAF) of 0.75 indicates that the large majority of personalization's influence on purchase intention is transmitted through usefulness, trust, and satisfaction rather than directly.

Table 5: Specific indirect (mediation) effects

Indirect path	β	95% CI	Mediation
AIP → PU → PI	0.13	[0.07, 0.20]	Partial
AIP → TR → PI	0.14	[0.08, 0.21]	Partial
AIP → CS → PI	0.18	[0.11, 0.26]	Partial
Total indirect effect	0.41	[0.32, 0.50]	—

5.5 Moderation analysis

The interaction term between personalization and perceived privacy risk was negative and significant for both customer satisfaction (β = −0.13, t = 2.74, P< 0.01) and purchase intention (β = −0.10, t = 2.09, P< 0.05), supporting H9a and H9b. A simple-slope analysis confirmed the pattern: the positive relationship between personalization and each outcome was substantially stronger for respondents one standard deviation below the privacy-risk mean than for that one standard deviation above it. In practical terms, the benefits of personalization are systematically attenuated among privacy-concerned consumers.

6. DISCUSSION

The results provide consistent support for the proposed model and yield three principal insights. First, AI-driven personalization is a meaningful driver of perceived usefulness, trust, and satisfaction, confirming that intelligent tailoring affects consumers through cognitive, relational, and affective channels rather than a single route. Second, and most notably, personalization's effect on purchase intention is overwhelmingly indirect: the modest direct path and the high variance-accounted-for indicate that personalization persuades not by itself but by making the platform feel useful, trustworthy, and satisfying. This integration of TAM and ECT, augmented by trust, helps reconcile mixed prior findings—personalization that is technically accurate but fails to build trust or satisfaction would be expected to underperform. Third, the negative moderation by perceived privacy risk confirms the personalization–privacy paradox in a contemporary AI context: the very capabilities that create relevance can provoke concern, and where privacy risk is high, personalization's benefits measurably erode. Personalization is therefore valuable but conditional, contingent on the perceived legitimacy and transparency of underlying data practices.

7. Theoretical and Managerial Implications

7.1 Theoretical implications

The study contributes an integrated, mechanism-level account of personalization effects, modelling perceived usefulness,

trust, and satisfaction as parallel mediators and perceived privacy risk as a moderator. By demonstrating that the indirect effects dominate the direct effect, it cautions against treating personalization as a self-evidently persuasive feature and supports the joint use of TAM and ECT with a relational trust pathway. The findings extend acceptance and satisfaction theory to AI-era personalization and provide a reusable measurement and analysis template for future replication and extension.

7.2 Managerial implications

For practitioners, the evidence sets clear priorities. Investment in recommendation quality is justified, but because the effect on intention is largely indirect, personalization should be designed to be visibly useful, trust-building, and satisfying rather than merely accurate. Relevance signals should be paired with transparency—clear consent, intuitive privacy controls, and explanations of why a recommendation appears—since the privacy-risk moderation shows that unmanaged concern directly erodes commercial returns. Managing privacy is thus not a compliance afterthought but a lever on the value of personalization itself.

8. LIMITATIONS AND FUTURE RESEARCH

Several limitations qualify these conclusions. The cross-sectional design captures associations at one point in time and cannot establish causality; longitudinal or experimental designs would strengthen causal inference. Self-reported intention is an imperfect proxy for behaviour, so future work should link survey constructs to actual transaction data. The sample was drawn from a single country using non-probability (purposive and snowball) methods, which constrains generalizability across cultures, platforms, and product categories and introduces possible self-selection bias; replication with probability samples and cross-national comparison is encouraged. The model also omits constructs that merit attention as the technology evolves, including perceived personalization "creepiness," algorithmic transparency and explainability (Shin, 2021) [16], and the emerging role of generative-AI shopping assistants.

9. CONCLUSION

This study examined whether and how AI-driven personalization shapes consumer purchase intention and customer satisfaction on e-commerce platforms. The evidence indicates that personalization exerts a positive influence operating largely through three complementary mechanisms—perceived usefulness, trust, and satisfaction—with only a modest direct effect, and that perceived privacy risk significantly attenuates these benefits. The practical message is balanced rather than triumphalist: personalization is a powerful instrument for growth, but its value is realised only when it is genuinely useful, trust-building, experienced as satisfying service, and governed by transparent data practices.

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