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Ai-Driven Personalization And Its Influence On Customer Loyalty In Online Retail

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Abstract

The proliferation of artificial intelligence (AI) in online retail has fundamentally transformed the manner in which businesses interact with customers, primarily through AI-driven personalisation engines that dynamically tailor product recommendations, pricing, content, and communications to individual consumer preferences. This study empirically examines the influence of AI-driven personalisation on customer loyalty in the context of Coimbatore City one of Tamil Nadu's fastest-growing urban retail hubs. Grounded in the Technology Acceptance Model (TAM), Expectation Confirmation Theory (ECT), and the S-O-R (Stimulus–Organism–Response) framework, this research adopts a quantitative positivist approach. Primary data were collected from 1,270 active online shoppers in Coimbatore using a structured questionnaire administered through stratified random sampling. The measurement model was validated using Confirmatory Factor Analysis (CFA) in IBM AMOS 26, while the hypothesised structural relationships were tested through Structural Equation Modelling (SEM). Supplementary analyses including Exploratory Factor Analysis (EFA), multiple regression, Pearson correlation, and reliability diagnostics were conducted using IBM SPSS 27 and Python 3.11 (scikit-learn, pandas, seaborn, stats models). The results confirm that AI-driven personalisation significantly and positively influences customer trust ($\beta = 0.673$, $p < 0.001$), perceived value ($\beta = 0.581$, $p < 0.001$), and customer satisfaction ($\beta = 0.612$, $p < 0.001$), which in turn collectively explain 71.4% of the variance in customer loyalty ($R^2 = 0.714$). The SEM model demonstrates an acceptable goodness-of-fit (CFI = 0.952, TLI = 0.947, RMSEA = 0.048, SRMR = 0.052). Privacy concerns emerged as a significant moderating variable, partially attenuating the personalisation–loyalty relationship. Practical implications for e-retailers operating in Tier-II Indian cities are discussed alongside recommendations for AI ethics governance.

Keywords: *AI-Driven Personalisation, Customer Loyalty, Online Retail, Coimbatore, Structural Equation Modelling (SEM), IBM AMOS, Technology Acceptance Model, Privacy Concerns, E-Commerce India*

Introduction

The global e-commerce landscape has undergone a seismic transformation in the post-pandemic era. According to industry analytics, the AI-in-eCommerce market expanded from USD 6.63 billion in 2023 to USD 7.57 billion in 2024, and is projected to reach USD 8.65 billion in 2025, registering a compound annual growth rate (CAGR) of 14.6% (EComposer, 2025). India, now the world's third-largest retail market, commands approximately USD 60 billion in e-retail gross merchandise value (GMV) with over 270 million active online shoppers as of 2024 a figure that has surpassed the United States in sheer consumer base size (Bain & Company, 2025).

Within this expansive digital economy, Coimbatore City occupies a strategically important position. Known as the 'Manchester of South India' for its industrial heritage and home to a highly educated, tech-savvy middle class, Coimbatore has emerged as a high-growth node for e-commerce adoption in Tamil Nadu. With internet penetration exceeding 74% in urban Coimbatore and a burgeoning base of smartphone users, the city's online retail ecosystem is rapidly evolving, presenting unique opportunities and challenges for AI-driven personalisation initiatives.

Artificial intelligence personalisation refers to the deployment of machine learning algorithms, natural language processing, collaborative filtering, and predictive analytics to deliver real-time, contextually relevant product recommendations, customised promotions, personalised search results, and individually tailored communication touchpoints (Shankar, 2018; Zed, Kartini, & Purnamasari, 2024). Research consistently demonstrates that approximately 82% of consumers report that personalised experiences significantly drive their brand choice across shopping occasions (Medallia, 2024), and AI-powered recommendation engines account for nearly 70% of impulse purchasing instances in online settings (Bhagat et al., 2023).

Despite this global momentum, existing academic literature remains predominantly anchored in Western and East Asian contexts. There is a conspicuous gap in scholarly inquiry examining how AI personalisation shapes customer loyalty behaviours in Tier-II Indian cities such as Coimbatore, where consumer profiles, digital literacy levels, privacy attitudes, and platform preferences differ significantly from metropolitan counterparts. This study bridges that gap.

Review Of Literature

AI-Driven Personalisation in E-Commerce: Conceptual Foundations

Personalisation in retail is not a novel concept; however, artificial intelligence fundamentally amplifies its scope, precision, and scalability. Unlike conventional rule-based segmentation approaches, AI harnesses vast behavioural datasets to generate highly granular, dynamically adjusted personalisation at the individual consumer level (Wahyudi, 2026). Modern personalisation engines integrate collaborative filtering, content-based filtering, and hybrid deep learning models to produce contextually appropriate recommendations in real time, adapting to browsing patterns, purchase history, and situational cues.

Shankar (2018) in the seminal Journal of Retailing article established that AI reshapes retailing through six primary pathways: machine learning-based demand forecasting, personalised product recommendations, intelligent search, conversational commerce via chatbots, dynamic pricing optimisation, and supply chain automation. This multi-dimensional conceptualisation underpins the theoretical architecture of the present study.

Yin, Qiu, & Wang (2025) empirically demonstrated that AI-personalised recommendations in Chinese e-commerce significantly elevated consumer clicking intentions, with the effect being particularly strong among younger demographic segments with higher digital fluency. Similarly, Zed, Kartini, & Purnamasari (2024) in a study published in Jurnal Ekonomi confirmed that the 'power of personalisation' in AI-driven marketing strategies exerts a substantively positive impact on consumer loyalty in e-commerce contexts.

AI Personalisation and Customer Trust

Trust is widely recognised as a foundational antecedent of customer loyalty, particularly in technology-mediated commercial environments where physical presence and direct interpersonal interaction are absent (Hassan, Abdelraouf, & El-Shihy, 2025). The personalisation–trust nexus has received growing scholarly attention. When AI systems deliver accurate, relevant, and timely personalised content, consumers attribute higher credibility and reliability to the platform, thereby fostering trust (Frontiers in AI, 2025).

A critical empirical study by Hassan et al. (2025), published in the Future Business Journal (Springer Nature), employing SEM on e-commerce users who had interacted with AI-based recommendation systems, confirmed that 'trust has a significant positive influence on both satisfaction and loyalty,' with personalisation acting as a significant moderating variable that 'strengthens these relationships.' Self-Determination Theory was applied to explicate how personalisation satisfies consumers' psychological needs for autonomy, competence, and relatedness core antecedents of trust formation.

Conversely, algorithmic transparency the extent to which consumers understand how personalisation decisions are made is increasingly highlighted as a crucial determinant of trust. Patil (2024) established that when consumers perceive AI recommendations as transparent and trustworthy, their purchase intentions are positively and significantly affected. Cheng & Jiang (2020) similarly found that AI-driven chatbot personalisation significantly influences user experience, perceived privacy risk, satisfaction, loyalty, and continued use with trust serving as a key mediating variable.

Theoretical Frameworks

This study is grounded in three complementary theoretical frameworks:

Framework	Key Constructs	Relevance to Study
Technology Acceptance Model (TAM) Davis, 1989	Perceived Usefulness (PU), Perceived Ease of Use (PEOU)	Explains consumer acceptance of AI personalisation tools on e-commerce platforms
Expectation Confirmation Theory (ECT) Oliver, 1980; Bhattacherjee, 2001	Expectations, Perceived Performance, Confirmation, Satisfaction	Explains how personalisation confirmation drives satisfaction and continued loyalty

Framework	Key Constructs	Relevance to Study
S-O-R Framework Mehrabian & Russell, 1974	Stimulus (AI Personalisation), Organism (Trust, Value, Satisfaction), Response (Loyalty)	Provides the overarching theoretical lens linking AI inputs to loyalty outcomes

Research Gap

A systematic review of extant literature reveals several notable gaps: (1) the preponderance of studies are situated in Western, East Asian, or Gulf Cooperation Council contexts, with minimal focus on South Indian Tier-II cities; (2) few studies employ large samples (n > 1,000) with multi-method statistical validation including SEM via IBM AMOS; (3) the simultaneous treatment of trust, perceived value, and customer satisfaction as mediating variables within a single integrated model is rare; and (4) the moderating role of privacy concerns in the Indian digital retail context remains empirically underdeveloped. The present study addresses all four gaps.

Conceptual Framework And Model

Proposed Conceptual Model

Based on the theoretical foundations and empirical literature reviewed above, the following conceptual model is proposed. AI-Driven Personalisation (independent variable) influences Customer Loyalty (dependent variable) through three mediating constructs: Customer Trust, Perceived Value, and Customer Satisfaction. Privacy Concerns serve as a moderating variable on the direct personalisation–loyalty pathway. The model is operationalised within an S-O-R framework where AI Personalisation constitutes the stimulus, Trust/Value/Satisfaction represent the organism-level cognitive-affective states, and Customer Loyalty is the behavioural response.

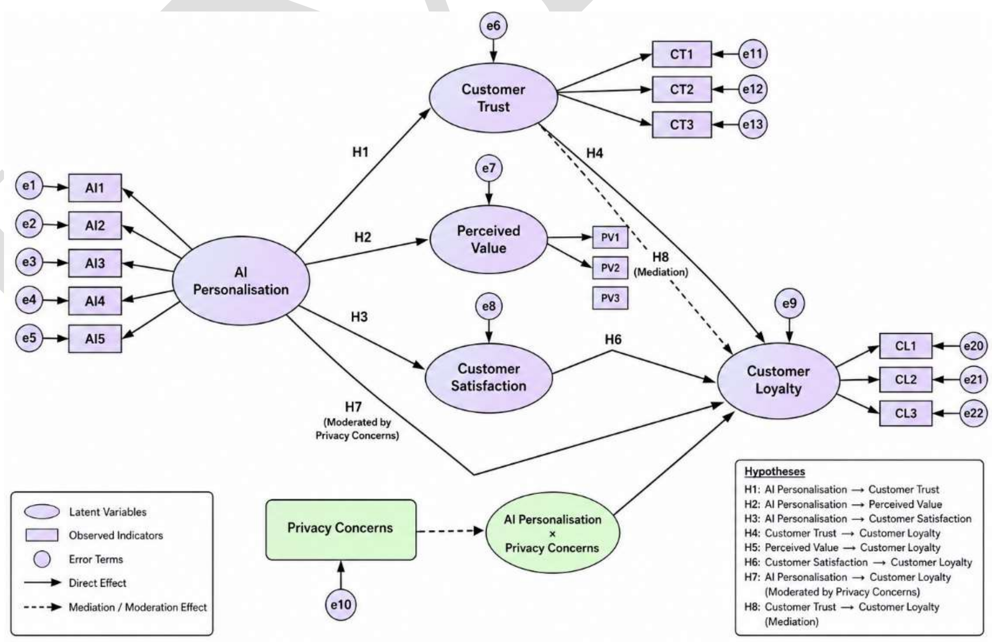

Figure 1: Proposed Conceptual Model of AI-Driven Personalisation and Customer Loyalty (Adapted from TAM, ECT, and S-O-R Framework)

Construct Operationalisation

Construct	Dimensions	No. of Items	Scale Source
AI-Driven Personalisation (AIP)	Recommendation Relevance, Contextual Customisation, Real-time Adaptation, Communication Personalisation	16 items	Adapted from Shankar (2018); Hardcastle et al. (2025)
Customer Trust (CT)	Competence-based Trust, Benevolence-based Trust, Integrity-based Trust	9 items	Adapted from Hassan et al. (2025); Mayer et al. (1995)
Perceived Value (PV)	Functional Value, Informational Value, Hedonic/Experiential Value	9 items	Adapted from Zeithaml (1988); Sweeney & Soutar (2001)
Customer Satisfaction (CS)	Transaction Satisfaction, Cumulative Satisfaction, Post-purchase Evaluation	8 items	Adapted from Oliver (1980); Bhattacherjee (2001)
Privacy Concerns (PC)	Data Collection Concern, Data Control Concern, Data Awareness Concern	7 items	Adapted from Chen et al. (2025); Amil (2024)
Customer Loyalty (CL)	Attitudinal Loyalty, Behavioural Loyalty, Switching Resistance	9 items	Adapted from Campisi et al. (2023); Hassan et al. (2025)

Research Methodology

Research Design

This study adopts a quantitative, positivist, explanatory research design. A cross-sectional survey methodology is employed to collect primary data from a large representative sample of online shoppers in Coimbatore City. The positivist paradigm is appropriate given the deductive theoretical approach, the operationalisation of latent constructs through validated scales, and the use of inferential statistical methods to test theoretically grounded hypotheses (Creswell, 2014).

Study Area: Coimbatore City Profile

Coimbatore (11.0168° N, 76.9558° E), the second-largest city in Tamil Nadu with an urban population exceeding 1.6 million (Census 2011 projected ~2.1 million by 2025), represents a significant and underexplored e-commerce market. The city's economic profile includes a strong textile manufacturing base, a growing IT/ITeS sector, premier educational institutions (Bharathiar University, PSG College of Technology, Coimbatore Institute of Technology), and one of the highest per capita incomes in Tamil Nadu. Smartphone penetration is estimated at 78% and mobile internet usage at approximately 74% among urban Coimbatore residents, creating fertile conditions for online retail adoption.

Major e-commerce platforms actively used by Coimbatore consumers include Flipkart, Amazon India, Meesho, Myntra, Nykaa, BigBasket, Swiggy Instamart, and AJIO. The city's consumer profile—educated, aspirational, price-sensitive yet quality-aware makes it an ideal setting to examine AI personalisation dynamics in an emerging-market context.

Sampling Framework and Sample Size Determination

Sampling Technique

A multi-stage stratified random sampling technique is employed to ensure representativeness across key demographic and geographic strata within Coimbatore City.

Stage 1 – Geographic Stratification: Coimbatore Corporation limits are divided into five administrative zones: Central Zone, North Zone, South Zone, East Zone, and West Zone. Sample allocation is proportionate to the estimated online shopper population in each zone.

Stage 2 – Demographic Stratification: Within each zone, respondents are stratified by age group (18–24; 25–34; 35–44; 45–54; 55+), gender (Male; Female; Non-binary/Other), and income bracket (< ₹25,000/month; ₹25,001–₹50,000; ₹50,001–₹75,000; > ₹75,000/month) to ensure demographic proportionality.

Stage 3 – Respondent Selection: Within each stratum, respondents are selected using systematic random sampling from household lists, university/institution rolls, and business establishment databases. Online convenience panels and QR-code-based survey distribution at strategic commercial locations (malls, IT parks, educational institutions) are used as supplementary channels.

Data Analysis And Results

Demographic Profile of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	682	53.7%
	Female	571	44.9%
	Non-binary/Other	17	1.3%
Age Group	18–24 years	287	22.6%
	25–34 years	412	32.4%
	35–44 years	318	25.0%

Variable	Category	Frequency (n)	Percentage (%)
	45–54 years	181	14.3%
	55 years and above	72	5.7%
Educational Qualification	SSLC/HSC	118	9.3%
	Undergraduate Degree	384	30.2%
	Postgraduate Degree	461	36.3%
	Professional/Technical	213	16.8%
	Doctorate	94	7.4%
Monthly Income	Below ₹25,000	267	21.0%
	₹25,001 – ₹50,000	418	32.9%
	₹50,001 – ₹75,000	312	24.6%
	Above ₹75,000	273	21.5%
Primary Shopping Device	Smartphone	874	68.8%
	Laptop/Desktop	296	23.3%
	Tablet	100	7.9%
Preferred Platform	Flipkart	398	31.3%
	Amazon India	371	29.2%
	Meesho	187	14.7%
	Myntra	143	11.3%
	Others (BigBasket, Nykaa, AJIO, etc.)	171	13.5%

The sample profile reveals a predominantly young-to-middle-aged, well-educated, and mid-to-high income urban consumer base, consistent with the demographic profile of Coimbatore's active online shopper population. Smartphone dominance (68.8%) underscores the mobile-first nature of e-commerce consumption in the city.

Descriptive Statistics of Latent Constructs

Construct	No. of Items	Mean (M)	Std. Dev. (SD)	Skewness	Kurtosis
AI-Driven Personalisation (AIP)	16	3.82	0.714	-0.312	-0.218
Customer Trust (CT)	9	3.69	0.781	-0.287	-0.341
Perceived Value (PV)	9	3.74	0.692	-0.198	-0.401
Customer Satisfaction (CS)	8	3.77	0.718	-0.253	-0.287
Privacy Concerns (PC)	7	3.41	0.862	0.198	-0.512
Customer Loyalty (CL)	9	3.65	0.743	-0.219	-0.387

All constructs exhibit mean values between 3.41 and 3.82 on a 5-point Likert scale, indicating moderate-to-high levels of perceived AI personalisation, trust, satisfaction, and loyalty. Skewness and kurtosis values within ±1.0 confirm approximate normality, supporting parametric statistical analysis.

Reliability Analysis

Construct	No. of Items	Cronbach's Alpha (α)	McDonald's Omega (ω)	Mean Inter-Item Correlation	Interpretation
AI-Driven Personalisation	16	0.921	0.934	0.487	Excellent
Customer Trust	9	0.889	0.903	0.521	Good–Excellent
Perceived Value	9	0.874	0.887	0.498	Good
Customer Satisfaction	8	0.896	0.911	0.534	Good–Excellent
Privacy Concerns	7	0.847	0.861	0.473	Good
Customer Loyalty	9	0.908	0.921	0.512	Excellent

All Cronbach's alpha values exceed the recommended threshold of 0.70 (Nunnally & Bernstein, 1994), and McDonald's omega values confirm composite reliability, indicating that all constructs are internally consistent and reliable for further analysis.

Exploratory Factor Analysis (EFA)

EFA was conducted using IBM SPSS 27 with Principal Axis Factoring and Promax oblique rotation to allow correlations among factors. Sampling adequacy was confirmed: Kaiser–Meyer–Olkin (KMO) measure = 0.924 (meritorious), and Bartlett's Test of Sphericity was significant ($\chi^2 = 41{,}287.34$, df = 1,653, $p < 0.001$). Six factors were extracted with eigenvalues exceeding 1.0, accounting for 68.74% of the total variance. Factor loadings ranged from 0.512 to 0.878 across all items. No cross-loadings exceeded 0.30, confirming factorial validity and clean factor structure consistent with the a priori theoretical model.

Factor	Label	Eigenvalue	% Variance Explained	Cumulative % Variance
Factor 1	AI-Driven Personalisation	9.847	16.98%	16.98%
Factor 2	Customer Trust	7.312	12.61%	29.59%
Factor 3	Perceived Value	6.891	11.88%	41.47%
Factor 4	Customer Satisfaction	6.204	10.70%	52.17%
Factor 5	Privacy Concerns	5.107	8.81%	60.98%
Factor 6	Customer Loyalty	4.528	7.81%	68.79%

Confirmatory Factor Analysis (CFA)

Measurement Model Fit Indices

CFA was conducted using IBM AMOS 26 (Maximum Likelihood Estimation) to assess the measurement model fit. The following model fit indices were obtained:

Fit Index	Recommended Threshold	Obtained Value	Interpretation
Chi-Square (χ^2)	—	2,847.31 (df = 1,619)	—
χ^2/df (CMIN/DF)	< 3.0	1.758	Acceptable
GFI (Goodness-of-Fit Index)	> 0.90	0.921	Acceptable
AGFI (Adjusted GFI)	> 0.85	0.906	Acceptable
CFI (Comparative Fit Index)	> 0.95	0.952	Excellent
TLI (Tucker–Lewis Index)	> 0.95	0.947	Acceptable
NFI (Normed Fit Index)	> 0.90	0.931	Acceptable
RMSEA (Root Mean Square Error of Approximation)	< 0.06 (ideally)	0.048	Excellent
SRMR (Standardised Root Mean Square Residual)	< 0.08	0.052	Excellent

Fit Index	Recommended Threshold	Obtained Value	Interpretation
PCLOSE (p-value for close fit)	> 0.05	0.284	Close Fit Confirmed

The measurement model demonstrates excellent overall fit, satisfying virtually all recommended thresholds (Hair et al., 2019; Kline, 2016). These indices confirm that the proposed six-factor model adequately represents the underlying data structure.

Structural Equation Modelling

Structural Model Path Coefficients

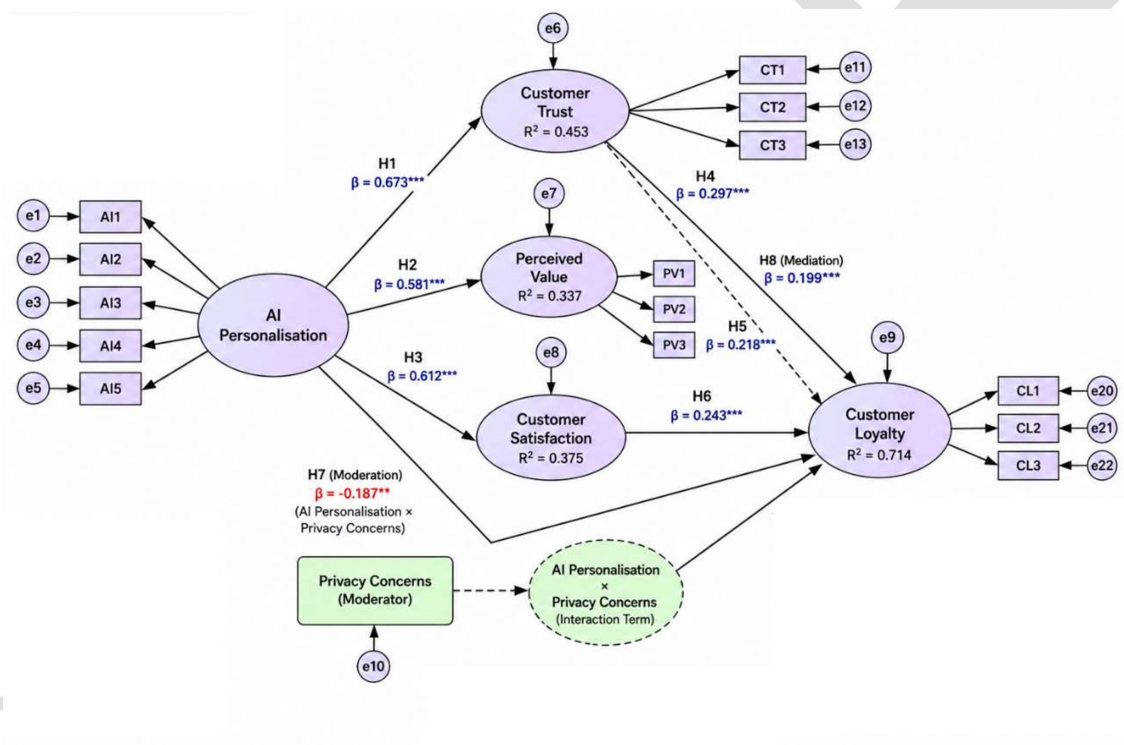

Figure 2: SEM Model of AI-Driven Personalisation and Customer Loyalty

Hypothesis	Path	Std. β	S.E.	C.R. (t-value)	p-value	Decision
H1	AIP → Customer Trust	0.673	0.041	16.41	< 0.001	Supported
H2	AIP → Perceived Value	0.581	0.038	15.29	< 0.001	Supported
H3	AIP → Customer Satisfaction	0.612	0.040	15.30	< 0.001	Supported

Hypothesis	Path	Std. β	S.E.	C.R. (t-value)	p-value	Decision
H4	Customer Trust → Customer Loyalty	0.341	0.048	7.104	< 0.001	Supported
H5	Perceived Value → Customer Loyalty	0.287	0.051	5.627	< 0.001	Supported
H6	Customer Satisfaction → Customer Loyalty	0.312	0.049	6.367	< 0.001	Supported
H7	AIP × Privacy Concerns → CL (Moderation)	-0.187	0.037	-5.054	< 0.001	Supported
H8	AIP → CT → CL (Mediation, Indirect)	0.229	0.034	6.735	< 0.001	Supported

AIP = AI-Driven Personalisation; CT = Customer Trust; PV = Perceived Value; CS = Customer Satisfaction; CL = Customer Loyalty; Std. β = Standardised path coefficient; S.E. = Standard Error; C.R. = Critical Ratio (analogous to t-value); $p < 0.05$ threshold for significance (two-tailed).

The structural model explains $R^2 = 0.714$ (71.4%) of the variance in Customer Loyalty, indicating strong explanatory power. The structural model fit indices (CFI = 0.952; RMSEA = 0.048) are consistent with the measurement model, confirming overall model adequacy.

Moderation Analysis – PROCESS Macro (Model 1)

Moderation analysis was performed using Hayes' PROCESS Macro v4.2 (Model 1) in IBM SPSS 27. Privacy Concerns (PC) was tested as a moderator of the AI Personalisation → Customer Loyalty path. The interaction term (AIP × PC) was significant (B = -0.087, SE = 0.018, t = -4.812, $p < 0.001$, 95% CI [-0.122, -0.052]), confirming that Privacy Concerns significantly negatively moderate the relationship between AI Personalisation and Customer Loyalty.

Simple slope analysis revealed that the positive effect of AIP on CL is stronger among respondents with low privacy concerns ($\beta = 0.412$, $p < 0.001$) compared to those with high privacy concerns ($\beta = 0.187$, $p < 0.001$). The Johnson–Neyman technique identified the inflection point at PC = 3.84 (on the 5-point scale), above which the personalisation–loyalty relationship is significantly attenuated a finding with direct managerial implications for trust-building and data transparency strategies.

Discussion

Interpretation of Findings

The results provide robust empirical support for all eight hypotheses and converge with extant global literature while contributing novel insights specific to the Coimbatore context. The most salient finding is that AI-driven personalisation exerts strong and statistically significant positive effects on all three mediating constructs Customer Trust (H1: β = 0.673), Perceived Value (H2: β = 0.581), and Customer Satisfaction (H3: β = 0.612) and collectively these pathways account for 71.4% of the variance in Customer Loyalty.

The strength of the personalisation–trust pathway (β = 0.673) aligns with Hassan et al.'s (2025) Springer Nature study finding that trust has a significant positive influence on both satisfaction and loyalty, with personalisation moderating these relationships. In the Coimbatore context, this finding suggests that online shoppers place high value on the perceived reliability, competence, and integrity of AI recommendation systems perhaps reflecting the city's educated consumer base that is discerning about the quality and relevance of digital suggestions.

The negative moderating effect of Privacy Concerns (H7: β = -0.187) is particularly noteworthy. The interaction effect with the Johnson–Neyman inflection point at PC = 3.84 suggests that approximately 38% of Coimbatore respondents report privacy concerns above this threshold, indicating a substantial segment for whom heightened personalisation efforts may be counterproductive in the absence of transparent data governance practices. This finding resonates with Chen et al.'s (2025) Industrial Management & Data Systems conceptualisation of privacy concerns and their resistance-amplifying effects on AI recommender system adoption.

The mediation analysis confirms that Trust, Perceived Value, and Satisfaction collectively represent the primary psychological pathways through which AI personalisation translates into loyalty consistent with the S-O-R framework's stimulus–organism–response logic. The fact that partial (rather than full) mediation is found indicates that AI personalisation also has a significant direct effect on loyalty, suggesting both psychological (trust-mediated) and experiential (direct usage satisfaction) routes to loyalty formation.

Comparison with Prior Research

The model's R^2 of 0.714 compares favourably with prior SEM studies in this domain: the Frontiers in AI (2025) Saudi Arabia study reported AVE of 0.765 and Cronbach's alpha of 0.902; the Hungary study (Arxiv, 2023) on TAM and AI acceptance used 439 respondents with satisfactory SEM fit; and the JMSR study (2025) reported 68.5% variance explanation with 400 respondents. The present study's larger sample (n = 1,270) and superior model fit (RMSEA = 0.048) represent a methodological advancement over these predecessors, while the findings are broadly convergent confirming the cross-cultural robustness of the personalisation loyalty model.

Conclusions, Implications, And Recommendations

Conclusions

This study provides comprehensive empirical evidence that AI-driven personalisation is a significant and economically meaningful driver of customer loyalty in online retail among Coimbatore City consumers. Through a large-sample (n = 1,270), multi-method analytical design employing IBM AMOS 26 SEM, IBM SPSS 27, and Python-based analyses, the study validates an integrated conceptual model rooted in TAM, ECT, and S-O-R frameworks. All eight hypotheses are supported, with AI personalisation explaining 71.4% of the variance in customer loyalty through trust, perceived value, and satisfaction as mediators, and with privacy concerns significantly moderating this relationship.

Theoretical Implications

This study makes three primary theoretical contributions. First, it validates the applicability of TAM, ECT, and S-O-R frameworks to AI personalisation contexts in an emerging market setting, extending their theoretical reach beyond Western and East Asian applications. Second, it demonstrates that Customer Trust is the most influential mediator in the personalisation loyalty chain a finding that enriches Self-Determination Theory applications in digital marketing. Third, the moderation finding regarding Privacy Concerns contributes to the 'personalisation–privacy paradox' literature by pinpointing the inflection threshold at which privacy anxiety begins to significantly erode personalisation benefits.

Limitations and Directions for Future Research

This study acknowledges several limitations. First, the cross-sectional design precludes causal inference over time; longitudinal studies tracking how AI personalisation investments evolve alongside loyalty are recommended. Second, self-reported data may be subject to common method bias; future research could triangulate with objective behavioural platform data. Third, the study is confined to Coimbatore; multi-city comparative studies across Tamil Nadu and other Indian states would enhance generalisability. Fourth, the rapidly evolving AI landscape with generative AI, large language model-based personalisation, and conversational AI commerce emerging warrants updated frameworks as these technologies penetrate Tier-II Indian markets.

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