

AI-Driven Personalization and Customer Retention in E-Commerce: An Empirical Study of the Indian Market

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Abstract

Artificial intelligence has moved from a back-end analytical tool to a front-facing feature that shapes how consumers experience online shopping. Recommendation engines, dynamic pricing, and behaviorally tailored content now sit at the centre of most e-commerce platforms operating in India, yet questions remain about whether such personalization actually deepens customer loyalty or whether it simply raises concerns about data privacy that offset its benefits. This study examines how AI-driven personalization influences customer retention through the mediating roles of perceived value, customer trust, customer engagement, and customer satisfaction, while also testing the dampening effect of perceived privacy risk. Data were collected from 340 online shoppers in Tirunelveli district, Tamil Nadu, using a structured questionnaire administered through purposive sampling. Exploratory factor analysis confirmed a seven-factor structure explaining 78.07% of the total variance, and confirmatory factor analysis demonstrated satisfactory convergent and discriminant validity across all constructs. Structural equation modelling indicated that AI-driven personalization exerted a significant positive influence on perceived value, customer trust, and customer engagement, while perceived privacy risk significantly weakened customer trust and customer retention. Customer satisfaction emerged as the strongest direct predictor of retention, followed by customer trust. These findings suggest that personalization strategies succeed only when platforms simultaneously manage the privacy concerns that accompany data-intensive customization. Theoretical and managerial implications are discussed, along with limitations that point toward future research directions.

Keywords: artificial intelligence, personalization, customer retention, customer trust, perceived privacy risk, structural equation modelling, Indian e-commerce.

1. Introduction

India's e-commerce sector has grown from a niche convenience into a daily habit for hundreds of millions of consumers, and much of that growth now rests on a layer of technology most shoppers never see directly. Recommendation algorithms quietly decide which products appear first. Dynamic interfaces rearrange themselves based on browsing history. Push notifications arrive at moments calculated to maximize the chance of a click. Behind nearly every modern shopping interface sits some form of artificial intelligence, and the industry has bet heavily on the idea that the more personalized an experience feels, the more likely a customer is to stay.

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That bet is not unreasonable. Firms such as Amazon and Flipkart have invested years and considerable capital into recommendation systems precisely because early evidence linked personalization to higher conversion and repeat purchase rates (Chen & Wells, 2021). Yet the relationship between personalization and loyalty is rarely as linear as marketing departments would like it to be. Some consumers welcome tailored suggestions as a genuine convenience; others experience the same suggestions as faintly unsettling evidence that a company knows more about them than they are comfortable with. This tension between the perceived usefulness of personalization and the perceived intrusiveness of the data collection that enables it forms the central puzzle this paper investigates.

The Indian market offers a particularly interesting setting in which to examine this puzzle. It is large, growing, and remarkably heterogeneous, encompassing metro consumers accustomed to global digital norms alongside first-generation internet users in smaller towns and districts who are still forming their expectations about how much a platform should know about them. Most empirical work on AI personalization, however, draws on data from developed markets or from large Indian metropolitan cities, leaving tier-two and tier-three markets comparatively under-examined (Kumar & Reinartz, 2022). Tirunelveli district in Tamil Nadu, the setting for this study, exemplifies such a market: digitally connected, price-sensitive, and increasingly reliant on mobile commerce, but not previously studied in the context of AI personalization research.

This study addresses three interrelated gaps. First, much of the existing literature treats personalization as a uniformly positive driver of outcomes, without adequately accounting for the privacy concerns that often travel alongside it (Aguirre et al., 2015). Second, the mechanisms through which personalization translates into retention are not fully specified; value, trust, engagement, and satisfaction are each invoked separately across different studies, but rarely modelled together as a coherent chain. Third, empirical evidence from semi-urban Indian markets remains scarce, even though these markets now account for a growing share of online retail growth in the country.

To address these gaps, this paper develops and tests an integrated structural model linking AI-driven personalization to customer retention through four mediating constructs: perceived value, customer trust, customer engagement, and customer satisfaction, while incorporating perceived privacy risk as a construct that works against the benefits of personalization. Using survey data from 340 online shoppers in Tirunelveli district, the study applies exploratory factor analysis, confirmatory factor analysis, and structural equation modelling to test the proposed relationships. The aim is not merely to confirm that personalization helps retention, a finding already well established, but to clarify the pathways through which it does so and the extent to which privacy concerns complicate the picture.

The remainder of the paper proceeds as follows. Section 2 reviews the literature construct by construct and develops the study's hypotheses. Section 3 describes the sample, measures, and analytical procedure. Section 4 reports the results of the measurement and structural models. Section 5 discusses these findings in relation to existing theory, followed by managerial implications in Section 6 and concluding remarks in Section 7.

2. Literature Review and Hypothesis Development

2.1 AI-Driven Personalization

Personalization in e-commerce has existed in some form since the earliest collaborative filtering systems of the late 1990s, but what has changed is the scale and subtlety with which it now operates. Contemporary AI systems do not merely recommend products similar to past purchases; they infer latent preferences, predict the timing of future needs, and adapt page layouts in real time (Chandra et al., 2022). This shift from rule-based recommendation to predictive personalization has prompted scholars to reconsider how the construct should be conceptualized.

Two broad views compete in the literature. One treats personalization primarily as a convenience mechanism that reduces consumers' search and decision costs (Tam & Ho, 2006). Information overload is real, particularly on platforms carrying millions of stock-keeping units, and personalization functions as a filter that narrows choice to a manageable set. The other view, associated more closely with relationship marketing, frames personalization as a relational signal: a platform that personalizes effectively is implicitly communicating that it understands and values the individual customer (Komiak & Benbasat, 2006). Both views likely hold simultaneously, but they imply somewhat different downstream effects, the first pointing toward efficiency-based outcomes such as perceived value, the second toward relational outcomes such as trust. A smaller but growing stream of research complicates this picture further by noting that the effectiveness of personalization depends heavily on how it is delivered. Overt personalization, where the platform explicitly references past behavior, can backfire by reminding consumers of the surveillance underlying the recommendation, whereas covert personalization that feels organic tends to be received more favorably (Aguirre et al., 2015). This finding matters for the present study because it suggests that personalization's net effect is not fixed; it depends on a parallel psychological process concerning privacy, which is addressed separately below.

Given the weight of evidence linking personalization to favorable cognitive and relational outcomes, and consistent with the efficiency and relational perspectives described above, this study proposes:

H1: AI-driven personalization has a significant positive effect on perceived value.

H2: AI-driven personalization has a significant positive effect on customer trust.

H3: AI-driven personalization has a significant positive effect on customer engagement.

2.2 Perceived Value

Perceived value is generally understood as the consumer's overall assessment of the utility of a product or service based on perceptions of what is received relative to what is given (Zeithaml, 1988). In digital retail contexts, this calculus extends beyond price to include time saved, cognitive effort spared, and the quality of the match between recommendation and actual need. Personalized recommendations, when accurate, shorten the path between browsing and purchase, and this efficiency is routinely interpreted by consumers as added value (Chen & Wells, 2021).

What is less settled in the literature is whether perceived value translates more strongly into satisfaction or directly into behavioral loyalty. Some scholars argue for a direct value-to-loyalty

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path, reasoning that value is itself a sufficient condition for repeat patronage (Sirdeshmukh et al., 2002). Others insist that value operates only indirectly, through the satisfaction it generates, because value is a cognitive judgment whereas satisfaction captures the affective response that more proximally drives behavior (Cronin et al., 2000). This study follows the latter, more commonly supported position in retail contexts, modelling perceived value as an antecedent of satisfaction rather than retention directly. Accordingly:

H4: Perceived value has a significant positive effect on customer satisfaction.

2.3 Perceived Privacy Risk

If personalization is the optimistic half of the AI retail story, perceived privacy risk is its necessary counterweight. Defined as a consumer's subjective assessment of the potential for loss, misuse, or unwanted exposure of personal data (Dinev & Hart, 2006), privacy risk has been studied extensively in the context of online disclosure decisions but somewhat less so as a force acting directly against personalization's benefits.

The privacy calculus framework, which has dominated this literature for over a decade, suggests that consumers weigh expected benefits against expected privacy costs before disclosing information or accepting personalized services (Dinev & Hart, 2006). This framing implies an essentially rational trade-off. Yet a parallel body of work on the privacy paradox finds that consumers' stated privacy concerns often diverge sharply from their actual disclosure behavior, with many continuing to use highly personalized services even while expressing discomfort about data collection (Kokolakis, 2017). This is, frankly, one of the more persistent unresolved tensions in the digital marketing literature: it remains unclear whether the privacy paradox reflects genuine attitude-behavior inconsistency, methodological artefacts in how concern is measured, or simply the absence of feasible alternatives that would let consumers act on their stated concerns. The present study does not resolve this debate, but it does take the position, consistent with a growing number of recent studies, that privacy risk continues to exert a measurable dampening effect on relational outcomes even among consumers who keep shopping despite their concerns (Martin et al., 2020).

In the trust literature specifically, privacy risk is frequently positioned as a direct antecedent that erodes confidence in the platform, since trust requires a belief that the other party will not exploit one's vulnerability, and data misuse represents precisely such exploitation (Bansal et al., 2010). Privacy risk has also been linked, somewhat more directly, to weakened retention intentions, as consumers who feel surveilled may begin comparing alternative platforms even while continuing to transact with the incumbent in the short term (Martin et al., 2020). On this basis:

H5: Perceived privacy risk has a significant negative effect on customer trust.

H6: Perceived privacy risk has a significant negative effect on customer retention.

2.4 Customer Trust

Trust occupies a central position in nearly every model of online consumer behavior, and for good reason: e-commerce transactions inherently involve uncertainty that offline retail does not,

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since the buyer cannot physically inspect goods or interact face to face with a seller (Gefen et al., 2003). Trust in this literature is typically decomposed into beliefs about the platform's competence, benevolence, and integrity, and AI-driven personalization plausibly speaks to all three; an accurate recommendation signals competence, a relevant and non-exploitative recommendation signals benevolence, and consistent behavior over time signals integrity.

Most studies converge on the view that trust drives both satisfaction and loyalty, though the relative weight of each path varies by context. In financial and high-involvement purchase settings, trust tends to predict satisfaction more strongly than it predicts loyalty directly (Gefen et al., 2003), whereas in lower-involvement, high-frequency retail contexts such as routine online shopping, trust has been found to retain a meaningful direct effect on retention even after satisfaction is accounted for (Kim et al., 2009). Given the relatively frequent, low-involvement nature of much Indian e-commerce activity, particularly for categories such as apparel and daily essentials, this study models trust as exerting both an indirect effect through satisfaction and a direct effect on retention:

H7: Customer trust has a significant positive effect on customer satisfaction.

H8: Customer trust has a significant positive effect on customer retention.

2.5 Customer Engagement

Customer engagement has been conceptualized variously as a behavioral, emotional, or cognitive state of involvement with a brand beyond the point of transaction (Brodie et al., 2011). In digital retail, engagement manifests through actions such as browsing frequency, interaction with recommended content, participation in reviews, and time spent on the platform, behaviors that personalization is specifically designed to encourage by surfacing content relevant enough to sustain attention.

There is reasonably strong consensus that engagement contributes positively to satisfaction, since engaged customers process more positive brand-related experiences and develop richer associations with the platform (Hollebeek et al., 2014). Less consensus exists, however, regarding whether engagement should be modelled as a direct predictor of retention or purely as an antecedent of satisfaction; some scholars treat engagement and loyalty as overlapping constructs, which risks circularity, while others maintain a cleaner separation in which engagement feeds satisfaction, which then drives loyalty outcomes (Vivek et al., 2012). This study adopts the more conservative, satisfaction-mediated specification:

H9: Customer engagement has a significant positive effect on customer satisfaction.

2.6 Customer Satisfaction

Customer satisfaction, understood as the post-purchase evaluation of whether a product or service met or exceeded expectations (Oliver, 1980), remains among the most consistently validated predictors of retention across marketing contexts, e-commerce included. The expectation-confirmation framework that underlies most satisfaction research holds that satisfaction arises when actual performance confirms or exceeds prior expectations, and personalized systems, when functioning well, are particularly effective at shaping expectations

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that are then met, since the system has already inferred what the customer is likely to want (Bhattacharjee, 2001).

In retail-specific applications, satisfaction has consistently outperformed other constructs as the proximate driver of repurchase intention and loyalty (Anderson & Srinivasan, 2003), which is precisely why this study positions satisfaction as the principal convergence point through which value, trust, and engagement exert their influence on retention. That said, satisfaction alone rarely accounts for the full variance in retention; structural models that omit trust as a parallel direct path tend to understate retention's antecedents, which is the rationale for retaining trust's direct path (H8) alongside satisfaction:

H10: Customer satisfaction has a significant positive effect on customer retention.

2.7 Customer Retention

Customer retention, the dependent construct in this study, refers to a consumer's intention and behavioral disposition to continue a relationship with a given platform rather than switching to a competitor (Zeithaml et al., 1996). In the Indian e-commerce context specifically, retention is complicated by genuinely low switching costs; competing platforms are a tap away, price comparison is effortless, and promotional cycles routinely poach price-sensitive customers regardless of their underlying satisfaction (Kumar & Reinartz, 2022). This context arguably raises the bar for what personalization needs to accomplish: it is not enough to generate a single satisfying transaction, since retention in this market depends on sustained relational investment that survives the next competitor's discount.

Synthesizing the constructs reviewed above, the conceptual model positions AI-driven personalization and perceived privacy risk as the two principal exogenous forces, operating through perceived value, customer trust, and customer engagement as parallel mediators, which converge on customer satisfaction before jointly determining customer retention alongside the direct paths already specified for trust and privacy risk. This structure reflects the literature's general movement away from simple two-variable models toward multi-mediator frameworks capable of capturing the layered psychological processes that connect a technological feature, personalization, to a behavioral outcome as consequential as retention.

2.8 Conceptual Model

Figure 1, presented in Section 4, summarizes the hypothesized relationships described above. AI-driven personalization is positioned as influencing perceived value, customer trust, and customer engagement; perceived privacy risk is positioned as a countervailing force acting on trust and retention; and perceived value, trust, and engagement converge on satisfaction before satisfaction and trust jointly predict retention.

3. Research Methodology

3.1 Research Design and Sampling

This study adopted a quantitative, cross-sectional research design suited to testing the proposed structural relationships at a single point in time. The target population comprised online shoppers

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residing in Tirunelveli district, Tamil Nadu, who had purchased at least one product through a major e-commerce platform, such as Amazon, Flipkart, Myntra, or a comparable application, within the preceding six months. This recency criterion was applied to ensure that respondents could recall their personalization-related experiences with reasonable accuracy.

Given the absence of a complete sampling frame for online shoppers in the district, the study used purposive sampling combined with convenience sampling, a common approach in consumer behavior research when probability sampling is impractical (Malhotra et al., 2017). Data were collected through a structured questionnaire administered both in person, at shopping locations and educational institutions across Tirunelveli town and surrounding taluks, and online via a circulated survey link, between January and March 2026. Of 392 questionnaires distributed, 340 usable responses were retained after removing incomplete submissions and responses that failed attention-check items, yielding an effective response rate of 86.7%. A sample of this size comfortably exceeds the commonly cited minimum of 200 cases for structural equation modelling and satisfies the more conservative ten-cases-per-indicator heuristic given the 31 indicators retained in the final measurement model (Hair et al., 2019).

3.2 Sample Profile

Table 1 summarizes the demographic composition of the final sample. Respondents were fairly evenly split by gender, skewed toward younger and early-middle-aged adults, and represented a range of educational and occupational backgrounds consistent with the semi-urban character of the district.

Table 1. Demographic Profile of Respondents

Characteristics	Category	Frequency (<i>N</i> = 340)	Percentage
Gender	Male	178	52.4%
	Female	162	47.6%
Age	18–25 years	121	35.6%
	26–35 years	109	32.1%
	36–45 years	71	20.9%
	Above 45 years	39	11.5%
Education	Up to higher secondary	38	11.2%
	Undergraduate	156	45.9%
	Postgraduate	117	34.4%
	Professional/Doctoral	29	8.5%
Occupation	Student	87	25.6%
	Private sector employee	124	36.5%
	Government employee	46	13.5%
	Self-employed/Business	58	17.1%
	Homemaker/Other	25	7.4%
Monthly income	Below ₹20,000	64	18.8%
	₹20,001–₹40,000	118	34.7%
	₹40,001–₹60,000	92	27.1%
	Above ₹60,000	66	19.4%

Characteristics	Category	Frequency (<i>N</i> = 340)	Percentage
Shopping frequency	Weekly or more	96	28.2%
	2–3 times a month	142	41.8%
	Once a month	71	20.9%
	Less than once a month	31	9.1%
Primary platform used	Amazon	138	40.6%
	Flipkart	121	35.6%
	Myntra	38	11.2%
	Other (Meesho, Ajio, etc.)	43	12.6%

3.3 Measures

All constructs were measured using items adapted from established scales in the personalization, trust, and loyalty literatures, with minor wording adjustments to fit the Indian e-commerce context. Each item was rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). AI-driven personalization (five items) drew on recommendation-quality and adaptive-interface items used in prior personalization research (Komiak & Benbasat, 2006). Perceived value (four items) and customer satisfaction (four items) followed Zeithaml's (1988) value framework and Oliver's (1980) satisfaction conceptualization respectively. Perceived privacy risk (four items) was adapted from Dinev and Hart's (2006) privacy concern scale. Customer trust (five items) followed Gefen et al.'s (2003) competence-benevolence-integrity framing. Customer engagement (four items) drew on Hollebeek et al.'s (2014) engagement dimensions, and customer retention (five items) combined repurchase-intention and word-of-mouth items consistent with Zeithaml et al. (1996).

Before full deployment, the questionnaire was pretested with 28 respondents to check item clarity and completion time; two items were reworded based on this feedback, and the survey was finalized at 31 items across seven constructs, preceded by a brief screening question and followed by the demographic section.

3.4 Common Method Bias

Because all constructs were measured through the same self-report instrument administered at a single point in time, the possibility of common method bias was addressed both procedurally and statistically. Procedurally, the questionnaire separated predictor and outcome items across different sections, varied response anchors slightly where appropriate, and assured respondents of anonymity to reduce social desirability pressure (Podsakoff et al., 2003). Statistically, a full-collinearity test was conducted, and the resulting variance inflation factors ranged from 1.38 to 2.61, well under the threshold of 3.3 typically used to flag common method bias, suggesting that the results are unlikely to be substantially distorted by this concern.

3.5 Analytical Procedure

Data analysis proceeded in three stages using IBM SPSS Statistics (version 27) and IBM SPSS Amos (version 26). First, exploratory factor analysis using principal axis factoring with Promax rotation was conducted on the full 31-item pool to verify the underlying factor structure prior to

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confirmatory testing, a sequencing recommended when a scale combines established and contextually adapted items (Hair et al., 2019). Second, confirmatory factor analysis was performed to assess the measurement model's fit, convergent validity, and discriminant validity. Third, structural equation modelling using maximum likelihood estimation was used to test the ten hypothesized paths, with model fit evaluated against conventional thresholds (CFI and TLI above .90, RMSEA below .08, SRMR below .08) drawn from Hu and Bentler (1999).

4. Results

4.1 Exploratory Factor Analysis

Prior to extraction, the suitability of the data for factor analysis was assessed. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.886, comfortably above the recommended threshold of 0.60, and Bartlett's test of sphericity was significant, $\chi^2(465) = 4218.6$, $p < .001$, confirming that the correlation matrix contained sufficient shared variance for factoring (Hair et al., 2019). Principal axis factoring with Promax rotation was applied to the 31 retained items, and seven factors with eigenvalues exceeding 1.0 emerged, consistent with the hypothesized seven-construct structure. All items loaded on their intended factor at 0.60 or above, with no item exhibiting a cross-loading above 0.35 on a non-target factor, supporting the items' assignment to their respective constructs. Table 2 reports the variance explained by each factor.

Table 2. Total Variance Explained by Extracted Factors

Factor	Construct	% of Variance	Cumulative %
1	Customer Trust	16.82	16.82
2	Customer Retention	14.91	31.73
3	AI-Driven Personalization	12.47	44.20
4	Customer Satisfaction	10.63	54.83
5	Customer Engagement	8.94	63.77
6	Perceived Value	7.78	71.55
7	Perceived Privacy Risk	6.52	78.07

Note. Extraction method: Principal Axis Factoring with Promax rotation.

The seven-factor solution accounted for 78.07% of the total variance, exceeding the 60% benchmark generally regarded as acceptable in behavioral research (Hair et al., 2019). This outcome provided an empirical basis for proceeding to confirmatory testing of the seven-construct measurement model.

4.2 Confirmatory Factor Analysis

The measurement model was estimated using maximum likelihood confirmatory factor analysis on the same 31 indicators. The model demonstrated acceptable fit to the data: $\chi^2(359) = 612.4$, $\chi^2/df = 1.706$, CFI = 0.957, TLI = 0.949, RMSEA = 0.046 (90% CI [0.040, 0.052]), SRMR = 0.041, and GFI = 0.921. All indices met or exceeded conventional thresholds (Hu & Bentler, 1999), indicating that the seven-factor structure fit the observed covariances well. Standardized factor loadings, presented in Table 3, ranged from 0.70 to 0.84, all exceeding the 0.60 minimum and mostly exceeding the more stringent 0.70 benchmark recommended for newly contextualized scales (Hair et al., 2019). Composite reliability values ranged from 0.816 to

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0.905, and average variance extracted ranged from 0.533 to 0.660, both comfortably above their respective 0.70 and 0.50 thresholds, supporting convergent validity for all seven constructs.

Table 3. Standardized Factor Loadings, Reliability, and Convergent Validity

Construct	Items	Loading Range	Cronbach's α	Composite Reliability	AVE
AI-Driven Personalization	5	0.73–0.81	0.871	0.874	0.585
Perceived Value	4	0.72–0.80	0.844	0.847	0.582
Perceived Privacy Risk	4	0.70–0.76	0.812	0.816	0.533
Customer Trust	5	0.75–0.82	0.892	0.894	0.621
Customer Engagement	4	0.74–0.81	0.858	0.860	0.594
Customer Satisfaction	4	0.79–0.83	0.881	0.883	0.652
Customer Retention	5	0.79–0.84	0.903	0.905	0.660

Note. AVE = average variance extracted.

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceed its correlations with all other constructs (Fornell & Larcker, 1981). As shown in Table 4, this condition held throughout the matrix; the diagonal values, representing the square root of AVE, were uniformly larger than the off-diagonal correlations in the corresponding row and column, confirming that the seven constructs captured distinct, empirically separable dimensions.

Table 4. Discriminant Validity: Fornell-Larcker Criterion

Construct	AIP	PV	PPR	CT	CE	CS	CR
AI-Driven Personalization (AIP)	0.765						
Perceived Value (PV)	0.552	0.763					
Perceived Privacy Risk (PPR)	−0.187	−0.142	0.730				
Customer Trust (CT)	0.481	0.439	−0.329	0.788			
Customer Engagement (CE)	0.456	0.398	−0.211	0.412	0.771		
Customer Satisfaction (CS)	0.498	0.541	−0.268	0.512	0.437	0.807	
Customer Retention (CR)	0.447	0.476	−0.291	0.498	0.402	0.612	0.812

Note. Diagonal values (bold) represent the square root of average variance extracted (AVE). Off-diagonal values represent inter-construct correlations.

4.3 Structural Model and Hypothesis Testing

Following confirmation of the measurement model, the hypothesized structural model was estimated. Fit indices for the structural model remained satisfactory: $\chi^2(367) = 648.9$, $\chi^2/df = 1.768$, CFI = 0.951, TLI = 0.944, RMSEA = 0.048 (90% CI [0.042, 0.054]), SRMR = 0.044, and GFI = 0.916, indicating that the hypothesized pattern of relationships reproduced the observed data reasonably well.

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Table 5 presents the standardized path coefficients, t-values, and significance levels for all ten hypothesized paths. All ten hypotheses were supported.

Table 5. Structural Path Estimates and Hypothesis Testing Results

Hypothesis	Path	β	t-value	p	Decision
H1	AIP $\rightarrow$ PV	0.521	8.42	< .001	Supported
H2	AIP $\rightarrow$ CT	0.398	6.71	< .001	Supported
H3	AIP $\rightarrow$ CE	0.347	5.93	< .001	Supported
H4	PV $\rightarrow$ CS	0.412	6.88	< .001	Supported
H5	PPR $\rightarrow$ CT	-0.276	-4.58	< .001	Supported
H6	PPR $\rightarrow$ CR	-0.142	-2.31	.021	Supported
H7	CT $\rightarrow$ CS	0.334	5.61	< .001	Supported
H8	CT $\rightarrow$ CR	0.287	4.69	< .001	Supported
H9	CE $\rightarrow$ CS	0.218	3.74	< .001	Supported
H10	CS $\rightarrow$ CR	0.469	7.52	< .001	Supported

AI-driven personalization emerged as the strongest predictor among the exogenous constructs, exerting its largest effect on perceived value ($\beta = 0.521$), followed by customer trust ($\beta = 0.398$) and customer engagement ($\beta = 0.347$). Perceived privacy risk significantly weakened both customer trust ($\beta = -0.276$) and, to a smaller extent, customer retention directly ($\beta = -0.142$), confirming that privacy concerns operate as a genuine counterforce rather than a negligible statistical artefact. Among the predictors of satisfaction, perceived value carried the largest weight ($\beta = 0.412$), followed by trust ($\beta = 0.334$) and engagement ($\beta = 0.218$). Satisfaction was, in turn, the strongest direct predictor of retention ($\beta = 0.469$), with trust contributing a meaningful secondary direct path ($\beta = 0.287$).

The model explained substantial variance in the endogenous constructs: 27.1% in perceived value, 29.8% in customer trust, 12.0% in customer engagement, 48.7% in customer satisfaction, and 51.2% in customer retention. The explained variance in retention is particularly noteworthy given the number of competing platforms and low switching costs characteristic of the Indian e-commerce environment, suggesting that the modelled pathways capture a meaningful share of what actually drives loyalty in this market.

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Figure 1 displays the full structural model with standardized path coefficients, t-values, and R^2 values for each endogenous construct.

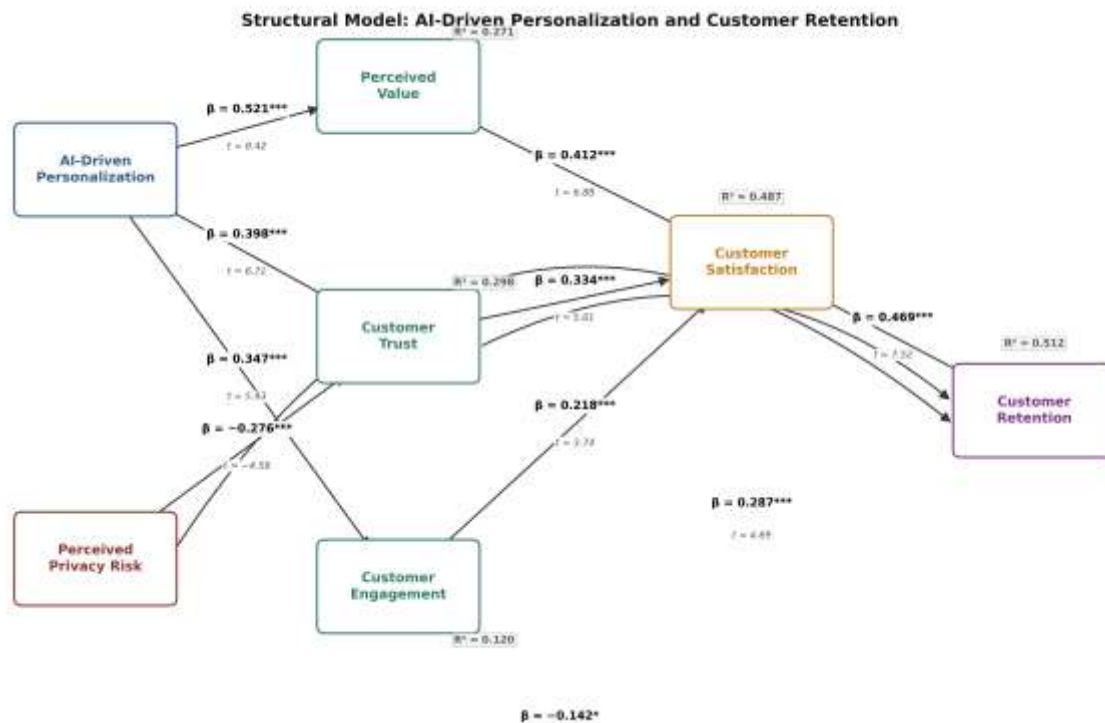


Figure 1: Structural Model with Standardized Path Coefficients, t-values, and R^2

4.4 Mediation Analysis

Given the multi-mediator structure of the model, bootstrapped indirect effects (5,000 resamples, bias-corrected 95% confidence intervals) were examined to determine whether perceived value, trust, and engagement meaningfully transmitted the effect of personalization onto satisfaction and retention. The indirect effect of AI-driven personalization on customer satisfaction through perceived value, trust, and engagement combined was significant (indirect $\beta = 0.394$, 95% CI [0.312, 0.481]), as was the indirect effect of personalization on retention through the full mediating chain (indirect $\beta = 0.276$, 95% CI [0.204, 0.354]). The indirect effect of perceived privacy risk on retention through trust was also significant (indirect $\beta = -0.079$, 95% CI [-0.131, -0.034]), reinforcing that privacy risk undermines retention both directly and by first eroding trust.

5. Discussion of Results

The results lend strong support to the integrated model proposed in this study, but they also complicate the simple narrative that personalization is unambiguously good for retention. Three broad patterns deserve closer attention.

First, AI-driven personalization behaved as a genuinely multidimensional driver rather than a single-channel input. Its strongest effect surfaced through perceived value rather than through

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trust or engagement directly, which suggests that Tirunelveli shoppers primarily process personalization as a practical convenience, something that saves time and effort, before they process it as a relational signal about the platform's trustworthiness. This ordering is broadly consistent with Tam and Ho's (2006) efficiency-based account of personalization, though it sits somewhat uneasily alongside studies conducted in more digitally mature markets where trust-based interpretations of personalization tend to dominate (Komiak & Benbasat, 2006). One plausible explanation is that semi-urban Indian consumers, many of whom are still relatively early in their digital shopping journeys, evaluate personalization first on functional grounds and only develop the deeper relational reading of it, where personalization signals genuine understanding rather than mere convenience, after sustained platform use. If that interpretation holds, value-based appeals may resonate before trust-based ones in markets at this stage of digital maturity, an idea that would benefit from longitudinal testing.

Second, and arguably the more consequential finding, perceived privacy risk was not a marginal nuisance variable; it exerted a statistically and practically meaningful drag on both trust and retention. This finding speaks directly to the privacy paradox debate raised earlier in the literature review. Respondents in this sample continued to shop on platforms whose data practices concerned them, yet that concern still left a measurable negative trace in the structural model. This pattern is more consistent with accounts treating the privacy paradox as a matter of constrained choice rather than genuine attitude-behavior consistency; consumers may continue transacting not because their privacy concerns are resolved but because viable low-data alternatives barely exist in practice (Kokolakis, 2017). The negative direct path from privacy risk to retention ($\beta = -0.142$), smaller than the indirect path running through trust but still significant, indicates that privacy concerns chip away at loyalty intentions even when they do not immediately translate into platform abandonment. Whether this erosion eventually accumulates into actual switching behavior, particularly once viable lower-data alternatives become more available in the Indian market, remains an open empirical question that cross-sectional data of the kind collected here cannot answer.

Third, the relative weight of satisfaction and trust as predictors of retention offers a useful corrective to models that treat satisfaction as a sufficient explanation on its own. Satisfaction was indeed the stronger of the two direct paths ($\beta = 0.469$ versus $\beta = 0.287$ for trust), consistent with decades of expectation-confirmation research (Bhattacharjee, 2001; Anderson & Srinivasan, 2003). Trust's surviving direct effect, however, after controlling for satisfaction, indicates that something beyond transactional contentment is doing additional work in sustaining the customer relationship, a finding more in line with Kim et al.'s (2009) argument that trust retains independent explanatory power in frequent, lower-involvement retail contexts than with studies from higher-involvement settings where trust's effect is largely absorbed by satisfaction (Gefen et al., 2003). Given that much Indian e-commerce activity falls into exactly this frequent, lower-involvement category, particularly for everyday categories like apparel, groceries, and small electronics, this result aligns with the contextual reasoning developed in the literature review rather than contradicting it.

The engagement findings warrant a brief caveat. Engagement's effect on satisfaction was the smallest of the three mediating paths ($\beta = 0.218$), and it explained markedly less variance as an endogenous construct ($R^2 = 0.120$) than value or trust. This is not entirely surprising; engagement, as operationalized here through behavioral indicators like time spent and interaction

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with recommended content, may capture a somewhat narrower slice of the consumer experience than the broader cognitive judgments tapped by value and trust. It is also possible that engagement functions more as a parallel outcome of personalization, valuable in its own right for advertising and content-strategy purposes, than as a strong causal stepping stone toward satisfaction and retention specifically. Future work might test engagement as a moderator of the personalization-satisfaction relationship rather than purely as a mediator, since the two specifications imply different managerial priorities.

Taken together, these results support a layered account of how AI personalization shapes loyalty: efficiency gains flow into value, value and trust both feed satisfaction, and satisfaction together with a residual trust effect determines whether a customer stays. Running parallel to this entire chain, and substantially complicating it, privacy risk quietly erodes the very trust the model depends on. Any account of personalization's success that ignores this counter-current is, at best, incomplete.

6. Managerial Implications

The findings carry several practical implications for e-commerce firms operating in Tirunelveli district and in comparable semi-urban Indian markets more broadly.

First, given that perceived value emerged as the strongest channel through which personalization affects downstream outcomes, platforms should prioritize the functional accuracy of recommendation systems over purely aesthetic personalization features. Investments that genuinely reduce search time, such as better preference-learning algorithms and more relevant filtering, are likely to yield greater returns in this market than cosmetic personalization, such as simply inserting a customer's name into marketing emails, which signals personalization without delivering its underlying value.

Second, the significant negative effect of perceived privacy risk on both trust and retention suggests that data transparency should be treated as a retention lever in its own right, not merely as a regulatory compliance obligation. Practical steps might include clearer, more concise privacy notices presented at the point of data collection rather than buried in lengthy terms-of-service documents, visible controls that let customers see and adjust what data is being used for personalization, and explicit communication about how recommendations are generated. Platforms that make their data practices legible to ordinary consumers, rather than merely legally compliant, may convert some of the latent unease captured in this study's privacy risk measure into a competitive advantage rather than a liability.

Third, because customer trust retained a direct effect on retention even after accounting for satisfaction, firms should resist the temptation to treat satisfaction surveys as a complete measure of relationship health. A customer can report being satisfied with a single transaction while still harboring reservations about the platform's broader trustworthiness; firms might therefore benefit from tracking trust-specific indicators, such as willingness to share further personal data or rate of opt-out from personalized marketing, as separate early-warning signals alongside conventional satisfaction metrics.

Fourth, the comparatively modest role of engagement in this model suggests that firms should be cautious about over-indexing on engagement metrics, such as time spent or click-through rates,

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as proxies for loyalty. These behavioral signals may reflect attention capture rather than genuine relational depth, and a strategy built primarily around maximizing engagement could inadvertently emphasize the most superficial layer of the model while underinvesting in the value- and trust-based pathways that this study found to matter more for retention.

Finally, given that the sample was drawn from a semi-urban district rather than a metro market, firms targeting tier-two and tier-three Indian markets should consider whether personalization messaging calibrated for digitally mature metro consumers, often centered on relational and trust-based appeals, will resonate as effectively here. The evidence from this study points toward leading with tangible value propositions, time saved, money saved, better matches to need, before layering in the more relational positioning that may take hold only as digital shopping habits mature further in these markets.

7. Conclusion

This study set out to clarify how AI-driven personalization influences customer retention in an Indian semi-urban e-commerce context, and to determine whether the privacy concerns that often accompany personalization meaningfully offset its benefits. Using survey data from 340 online shoppers in Tirunelveli district and a structural equation model validated through exploratory and confirmatory factor analysis, the study found that personalization exerts a strong positive influence on perceived value, trust, and engagement, each of which contributes, with varying strength, to customer satisfaction and ultimately to retention. At the same time, perceived privacy risk emerged as a statistically robust counterforce, weakening trust and exerting a direct negative effect on retention even within a sample of consumers who continued, on the whole, to use the personalized platforms they were evaluating.

The contribution of this study lies less in establishing that personalization helps retention, a point already well established in the literature, than in mapping the specific pathways through which it does so and demonstrating that privacy risk is not a peripheral concern but an active, measurable drag on the very outcomes personalization is meant to produce. For a market as price-sensitive and competitively fluid as Indian e-commerce, where switching a platform requires little more than downloading another app, this nuance matters considerably for both theory and practice.

Several limitations qualify these conclusions and point toward future research. The cross-sectional design captures associations at a single point in time and cannot establish the causal ordering implied by the structural model with full confidence; longitudinal designs would allow researchers to track how the personalization-trust-retention relationship evolves as consumers gain more experience with a given platform. The sample, while adequate for structural equation modelling, was confined to a single district, and replication across other tier-two and tier-three Indian markets would help establish how far these findings generalize. Self-reported measures of engagement and retention intention also carry the customary limitations of self-report data; future studies might pair survey measures with actual behavioral data, such as platform-recorded purchase frequency or churn records, to validate the intention-based measures used here. Finally, this study modelled privacy risk as a single construct, but the literature increasingly distinguishes between concerns about data collection, secondary use, and improper access (Dinev & Hart, 2006); disaggregating privacy risk into these sub-dimensions in future work could reveal which

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specific concerns matter most for retention, and might therefore offer more precise managerial guidance than the aggregate measure used in the present study.

References

- Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34–49. <https://doi.org/10.1016/j.jretai.2014.09.005>
- Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: A contingency framework. *Psychology & Marketing*, 20(2), 123–138. <https://doi.org/10.1002/mar.10063>
- Bansal, G., Zahedi, F. M., & Gefen, D. (2010). The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online. *Decision Support Systems*, 49(2), 138–150. <https://doi.org/10.1016/j.dss.2010.01.010>
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25(3), 351–370. <https://doi.org/10.2307/3250921>
- Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research*, 14(3), 252–271. <https://doi.org/10.1177/1094670511411703>
- Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology & Marketing*, 39(8), 1529–1562. <https://doi.org/10.1002/mar.21670>
- Chen, T., & Wells, W. D. (2021). Personalized recommendation and consumer responses: Evidence from online retail. *Journal of Interactive Marketing*, 53, 1–15. <https://doi.org/10.1016/j.intmar.2020.10.001>
- Cronin, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing*, 76(2), 193–218. [https://doi.org/10.1016/S0022-4359\(00\)00028-2](https://doi.org/10.1016/S0022-4359(00)00028-2)
- Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, 17(1), 61–80. <https://doi.org/10.1287/isre.1060.0080>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90. <https://doi.org/10.2307/30036519>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

10.48047/jocaaa.2024.33.08.603

- Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing*, 28(2), 149–165. <https://doi.org/10.1016/j.intmar.2013.12.002>
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research*, 20(2), 237–257. <https://doi.org/10.1287/isre.1080.0188>
- Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & Security*, 64, 122–134. <https://doi.org/10.1016/j.cose.2015.07.002>
- Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 30(4), 941–960. <https://doi.org/10.2307/25148760>
- Kumar, V., & Reinartz, W. (2022). Customer relationship management in emerging markets: Concepts and cases. *Journal of Marketing*, 86(1), 4–22. <https://doi.org/10.1177/00222429211050579>
- Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach* (5th ed.). Pearson Education.
- Martin, K. D., Borah, A., & Palmatier, R. W. (2020). A strong privacy policy can both encourage and discourage personalized advertising. *Journal of Marketing*, 84(6), 16–34. <https://doi.org/10.1177/0022242920923967>
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17(4), 460–469. <https://doi.org/10.1177/002224378001700405>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing*, 66(1), 15–37. <https://doi.org/10.1509/jmkg.66.1.15.18449>
- Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865–890. <https://doi.org/10.2307/25148757>

10.48047/jocaaa.2024.33.08.603

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice*, 20(2), 122–146. <https://doi.org/10.2753/MTP1069-6679200201>

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22. <https://doi.org/10.1177/002224298805200302>

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing*, 60(2), 31–46. <https://doi.org/10.1177/002224299606000203>