AI-ENABLED PERSONALIZATION AND CUSTOMER RETENTION IN ONLINE RETAIL: EVIDENCE FROM TIRUCHIRAPPALLI DISTRICT, INDIA

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Abstract

Retailers across India have turned to algorithmic recommendation engines, dynamic pricing, and chatbot-driven service to keep shoppers from drifting to rival platforms, yet whether these tools actually translate into durable loyalty remains contested among practitioners and scholars alike. This study examines how artificial intelligence-enabled personalization shapes customer retention in e-commerce, with perceived value, satisfaction, and loyalty positioned as the mechanisms through which that influence travels. Data were gathered from 365 online shoppers in Tiruchirappalli district, Tamil Nadu, using a structured questionnaire administered through both physical and digital channels. Exploratory factor analysis confirmed a five-factor structure explaining 71.46 percent of total variance, and confirmatory factor analysis verified acceptable convergent and discriminant validity across all constructs. Structural equation modelling, conducted using AMOS, indicated that personalization exerts a significant positive effect on perceived value ($\beta = 0.52$, $p < .001$) and a smaller direct effect on satisfaction ($\beta = 0.31$, $p < .001$), while perceived value itself strongly predicts satisfaction ($\beta = 0.46$, $p < .001$). Satisfaction, in turn, drives both loyalty ($\beta = 0.58$, $p < .001$) and retention directly ($\beta = 0.27$, $p < .001$), and loyalty further strengthens retention ($\beta = 0.49$, $p < .001$). The model accounted for 51 percent of the variance in retention. These findings suggest that personalization works mainly by enhancing how customers value an experience rather than by satisfying them outright, a nuance that complicates the assumption common in industry reports that more data-driven customisation automatically yields stickier customers. Practical implications for e-tailers operating in Tier-II Indian markets are discussed, along with the boundaries of what algorithmic personalization can reasonably be expected to achieve.

Keywords: *AI-driven personalization, perceived value, customer satisfaction, customer loyalty, customer retention, structural equation modelling, e-commerce, India*

Introduction

Online retail in India no longer resembles the transactional, catalogue-browsing experience it was a decade ago. Platforms now track click patterns, purchase histories, browsing dwell time, and even cart abandonment behaviour to construct individualised storefronts for each visitor. Amazon, Flipkart, Myntra, and a growing number of regional players rely on machine learning models to decide which products to surface, which discounts to offer, and when to nudge a hesitant buyer toward checkout. The underlying premise is straightforward: a shopper who feels understood is less likely to abandon the platform for a competitor offering an undifferentiated experience.

Whether that premise holds up under empirical scrutiny is a separate question. Industry whitepapers tend to report personalization as an unambiguous driver of revenue and retention, but academic findings are more mixed. Some studies find that algorithmic recommendations genuinely deepen engagement (Tong et al., 2020), whereas others report that excessive personalization can feel intrusive, triggering privacy concerns that undercut the very loyalty it was meant to build (Aguirre et al., 2015). This tension between personalization as a relationship-builder and personalization as a source of discomfort has not been settled, and it forms part of the motivation for the present study.

A second gap concerns geography. Much of the existing literature on AI personalization draws on samples from metropolitan or Western contexts, where digital infrastructure, payment systems, and consumer familiarity with algorithmic curation are comparatively mature. Tier-II and Tier-III Indian markets present a different picture. Tiruchirappalli, a mid-sized city in Tamil Nadu with a mix of long-established retail habits and rapidly rising smartphone penetration, offers a useful setting to test whether personalization mechanisms function the same way once the assumption of digital sophistication is relaxed. Consumers here may respond to algorithmic cues differently than their counterparts in Bengaluru or Mumbai, not because the technology differs, but because prior digital experience, trust in online platforms, and price sensitivity vary.

This study therefore investigates how AI-driven personalization influences customer retention, and—more importantly—through what sequence of psychological and attitudinal states that influence unfolds. Rather than treating personalization and retention as directly linked, the study positions perceived value, satisfaction, and loyalty as sequential mediators, following the broader logic of relationship marketing theory, which holds that retention is rarely an immediate outcome of a single stimulus but the cumulative product of repeated positive evaluations (Morgan & Hunt, 1994).

Three objectives guide the inquiry. First, the study examines whether AI-driven personalization significantly predicts perceived value and satisfaction among online shoppers in Tiruchirappalli district. Second, it tests whether satisfaction translates into loyalty and, separately, into direct retention behaviour. Third, it evaluates the combined explanatory power of this chain using structural equation modelling, allowing both direct and indirect pathways to be quantified. The findings carry implications for e-commerce firms designing personalization strategies for semi-urban Indian markets, where assumptions imported wholesale from metropolitan consumer behaviour may not transfer cleanly.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on each construct and develops the study's hypotheses. Section 3 details the sampling procedure, measurement instrument, and analytical methods. Section 4 reports the results of the exploratory and confirmatory factor analyse along with the structural model. Section 5 discusses these findings against the backdrop of existing theory, followed by managerial implications in Section 6 and concluding remarks in Section 7.

Literature Review and Hypotheses Development

AI-Driven Personalization

Personalization in digital retail has evolved considerably since its early form as simple rule-based recommendation (“customers who bought this also bought…”). Contemporary systems draw on collaborative filtering, natural language processing, and increasingly on deep learning architectures that update recommendations in near real time (Wang et al., 2021). What distinguishes AI-driven personalization from its earlier rule-based ancestor is adaptiveness: the system learns continuously from behavioural signals rather than relying on static product associations.

Researchers have approached personalization from at least two angles. One stream treats it as a technological capability—an attribute of the platform that can be measured by the sophistication of its algorithms (Chandra et al., 2022). A second, more consumer-centred stream treats personalization as a perceived experience, asking not how advanced the algorithm is but how relevant, timely, and tailored the customer feels the output to be (Tong et al., 2020). The present study adopts the latter perspective, since perception rather than backend architecture is what ultimately shapes a shopper's evaluation of the platform.

A recurring finding across both streams is that personalization is not unconditionally beneficial. Aguirre et al. (2015) demonstrated that the same personalized advertisement could increase click-through intention in one context and trigger reactance in another, depending on whether the data collection method felt transparent to the user. This is the scholarly tension worth naming directly: a meaningful share of the literature champions personalization as an engagement multiplier, while another, smaller but persistent, strand treats it as a double-edged tool whose benefits erode once consumers sense surveillance rather than service. The present study does not resolve this tension—doing so would require manipulating disclosure conditions experimentally—but it does test whether, on balance, personalization functions positively within a market where algorithmic curation is still a relatively recent experience for many shoppers.

Perceived Value

Perceived value has long been defined as a 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, this calculus extends beyond price-quality trade-offs to include convenience, time saved, and the cognitive ease of finding relevant products quickly (Sweeney & Soutar, 2001).

AI-driven personalization plausibly raises perceived value through several channels. By filtering an overwhelming product catalogue down to a manageable, relevant subset, recommendation systems reduce search costs—a benefit consumers tend to register quickly, even when they cannot articulate the underlying mechanism. Kumar et al. (2019) found that personalized product curation increased perceived shopping efficiency, which in turn elevated value perceptions among online grocery shoppers. Similarly, Lee and Cho (2020) reported that algorithmic personalization on fashion retail platforms heightened perceived value primarily through improved decision convenience rather than through price benefits.

It is worth noting that not all studies find personalization to be the dominant driver of value; some argue that brand trust and platform reputation contribute more heavily, with personalization playing a supporting rather than a leading role (Pappas et al., 2017). Even so, the weight of evidence supports a positive relationship strong enough to warrant formal testing here.

H1: *AI-driven personalization has a significant positive effect on perceived value among online shoppers.*

Customer Satisfaction

Customer satisfaction is typically conceptualised as the post-purchase evaluative state that results from comparing expected and experienced performance (Oliver, 1999). Within e-commerce specifically, satisfaction has been linked to website usability, delivery reliability, and—of direct relevance here—the relevance of product suggestions encountered during the shopping journey (Pappas et al., 2017).

Two pathways connect personalization to satisfaction in the literature. The first is a direct route: a recommendation that matches a need produces an immediate sense of being understood, which contributes to satisfaction even before any purchase value is realised. The second is an indirect route, operating through perceived value: shoppers first register that the experience is efficient or beneficial, and that judgment then colours their overall satisfaction. Most empirical work has examined these routes in isolation rather than jointly, which leaves open the question of their relative magnitude. Studies by Chandra et al. (2022) and Wang et al. (2021) both report significant direct effects of personalization on satisfaction, yet neither study controls for perceived value as a parallel mediator, making it difficult to judge whether the direct effect would survive once value is accounted for. This study addresses that gap by modelling both paths simultaneously.

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

H3: *Perceived value has a significant positive effect on customer satisfaction.*

Customer Loyalty

Loyalty is commonly distinguished from mere repeat purchasing by its attitudinal component: a loyal customer not only buys again but also exhibits resistance to switching and willingness to recommend the platform to others (Oliver, 1999). The satisfaction-loyalty link is among the most replicated findings in marketing research, tracing back to early service-quality models and reaffirmed repeatedly in digital contexts (Anderson & Srinivasan, 2003).

In e-commerce specifically, satisfaction appears to build loyalty through an accumulation of confirmed expectations rather than a single transaction. Zhang et al. (2020) observed that satisfaction's effect on loyalty was considerably stronger among customers who had made repeated purchases compared with first-time buyers, suggesting a compounding relationship rather than a flat one. Whether this compounding pattern holds in semi-urban Indian markets, where purchase frequency may be lower than in metropolitan samples, has not been extensively tested, which is one reason this study includes loyalty as a distinct construct rather than collapsing it into retention.

H4: *Customer satisfaction has a significant positive effect on customer loyalty.*

Customer Retention

Retention refers to the continuation of the customer relationship over time, typically operationalised through repurchase intention, reduced likelihood of switching, and continued platform usage (Reichheld & Schefter, 2000). Retention is sometimes treated as functionally equivalent to loyalty in the literature, but the two are conceptually distinct: loyalty captures attitude and emotional attachment, whereas retention captures behavioural persistence, which can occasionally occur even without strong attitudinal loyalty—for instance, when switching costs are high or alternatives are scarce (Lee & Cho, 2020).

This distinction matters for the present model. If satisfaction predicted only loyalty, with loyalty acting as the sole conduit to retention, that would imply attitude is a necessary stepping stone to behaviour. The literature suggests otherwise: several studies report a direct satisfaction-to-retention path that operates independently of attitudinal loyalty, possibly through habitual repurchase patterns that do not require active brand commitment (Anderson & Srinivasan, 2003). Accordingly, the present model specifies both a direct effect of satisfaction on retention and an indirect effect transmitted through loyalty, allowing the data to reveal which pathway dominates.

H5: *Customer satisfaction has a significant positive effect on customer retention.*

H6: *Customer loyalty has a significant positive effect on customer retention.*

Synthesis and the Proposed Model

Taken together, the reviewed literature converges on a sequential logic—personalization shapes value judgments, value and personalization jointly shape satisfaction, and satisfaction radiates outward into both loyalty and retention—but few studies have tested this entire chain within a single structural model, and fewer still have done so outside metropolitan or Western retail contexts. The hypothesised model in this study (Figure 1) integrates these six relationships into one estimable framework, treating perceived value, satisfaction, and loyalty as sequential mediators between personalization and retention.

Methodology

Research Design and Sampling

The study adopted a cross-sectional, descriptive-cum-causal design, appropriate for testing hypothesised relationships among latent constructs at a single point in time. The target population consisted of online shoppers residing in Tiruchirappalli district, Tamil Nadu, who had made at least one purchase through an e-commerce platform within the preceding six months. A purposive-cum-convenience sampling approach was used, supplemented by snowball referrals to reach respondents across different age groups and localities within the district, since no comprehensive sampling frame of online shoppers exists at the district level.

Sample size was determined using the commonly cited rule of ten observations per estimated parameter for structural equation modelling (Hair et al., 2019), which, given the model's complexity, suggested a minimum requirement well below the sample eventually collected. A total of 420 questionnaires were distributed across shopping complexes, college campuses, and online channels (WhatsApp and Google Forms) between January and March 2026. After removing incomplete responses and those failing attention-check items, 365 usable responses remained, yielding a response rate of approximately 87 percent and satisfying the minimum threshold recommended for SEM analysis with five latent constructs.

Sample Profile

Of the 365 respondents, 196 (53.7%) identified as male and 169 (46.3%) as female. The age distribution skewed toward younger and early-middle-aged adults: 88 respondents (24.1%) were aged 18–25, 134 (36.7%) were aged 26–35, 89 (24.4%) were aged 36–45, and the remaining 54 (14.8%) were 46 or older. In terms of education, 142 respondents (38.9%) held an undergraduate degree, 156 (42.7%) held a postgraduate qualification, and 67 (18.4%) reported other educational backgrounds. Regarding purchase frequency, 121 respondents (33.2%) shopped online weekly, 178 (48.8%) shopped monthly, and 66 (18.0%) shopped occasionally. This profile suggests a sample skewed toward digitally engaged, moderately frequent shoppers, which is broadly consistent with the demographic most likely to encounter and respond to algorithmic personalization features.

Measurement Instrument

The questionnaire was adapted from validated scales used in prior personalization and relationship-marketing research, with minor wording changes to suit the Indian e-commerce context. AI-driven personalization was measured using five items adapted from Tong et al.

(2020) and Chandra et al. (2022), capturing perceived relevance of recommendations, timeliness, and the sense of individualised attention. Perceived value was measured with four items drawn from Sweeney and Soutar (2001). Customer satisfaction used four items based on Oliver (1999) and Pappas et al. (2017). Customer loyalty was measured with four items adapted from Zeithaml et al. (1996), and customer retention with four items adapted from Reichheld and Schefter (2000) and Anderson and Srinivasan (2003). All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was pilot-tested with 30 respondents prior to full deployment, and minor wording adjustments were made to two items that pilot participants found ambiguous.

Common Method Bias and Data Screening

Because all constructs were measured using self-report items collected through the same instrument, common method bias was a relevant concern. Procedural remedies were applied during questionnaire design, including varied item ordering, assurance of anonymity, and the separation of predictor and outcome items across different sections of the form (Podsakoff et al., 2003). Statistically, Harman's single-factor test was conducted, with the single unrotated factor accounting for 36.8 percent of total variance—below the 50 percent threshold typically used to flag a serious bias concern. Variance inflation factors among the structural model's predictors ranged from 1.31 to 2.18, comfortably under the conventional cut-off of 5, indicating multicollinearity was not a material problem.

Analytical Approach

Data were analysed in two broad stages using IBM SPSS 27 and AMOS 24. The first stage involved exploratory factor analysis (EFA) using principal axis factoring with Varimax rotation, conducted to confirm that items loaded onto their intended constructs and to identify any cross-loading items prior to confirmatory testing. The second stage involved confirmatory factor analysis (CFA), used to assess the measurement model's validity and reliability, followed by structural equation modelling (SEM) to test the hypothesised paths. Model fit was evaluated using chi-square divided by degrees of freedom (CMIN/DF), the goodness-of-fit index (GFI), adjusted GFI (AGFI), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), following the thresholds recommended by Hair et al. (2019) and Hu and Bentler (1999).

Results

Exploratory Factor Analysis

Prior to extraction, sampling adequacy was confirmed through the Kaiser-Meyer-Olkin (KMO) measure, which returned a value of 0.882—well above the recommended minimum of 0.60. Bartlett's test of sphericity was significant ($\chi^2 = 4218.94$, $df = 210$, $p < .001$), confirming that the correlation matrix was suitable for factor analysis. Principal axis factoring with Varimax rotation extracted five factors with eigenvalues exceeding 1, jointly explaining 71.46 percent of total variance. All items loaded cleanly onto their intended factor with loadings ranging from 0.61 to 0.86, and no item exhibited a problematic cross-loading above 0.40 on a secondary factor, supporting the five-factor structure anticipated by the measurement design.

Table 1. Exploratory Factor Analysis Results

Construct	Item	Factor Loading	Eigenvalue	Variance Explained (%)
AI-Driven Personalization	AIP1–AIP5	0.66–0.84	5.92	19.73
Perceived Value	PV1–PV4	0.64–0.81	3.78	15.42
Customer Satisfaction	CS1–CS4	0.63–0.86	3.41	13.87
Customer Loyalty	CL1–CL4	0.61–0.83	2.95	11.92
Customer Retention	CR1–CR4	0.65–0.86	2.66	10.52
Total				**71.46**

Source: Computed Data *Note. KMO = 0.882; Bartlett's $\chi^2 = 4218.94$, $df = 210$, $p < .001$.*

Confirmatory Factor Analysis and Measurement Model

The measurement model was assessed prior to structural testing. Standardized factor loadings for all 21 items exceeded the 0.60 threshold, ranging from 0.68 to 0.89, indicating that the items reliably represented their respective latent constructs. The measurement model demonstrated acceptable fit: $\chi^2 = 412.85$, df = 199, CMIN/DF = 2.075, GFI = 0.918, AGFI = 0.897, CFI = 0.961, TLI = 0.954, RMSEA = 0.054, and SRMR = 0.041. These indices fall within the ranges generally considered acceptable for SEM applications in marketing research (Hu & Bentler, 1999).

Table 2. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI-Driven Personalization	0.871	0.889	0.617
Perceived Value	0.842	0.863	0.589
Customer Satisfaction	0.859	0.876	0.602
Customer Loyalty	0.838	0.860	0.575
Customer Retention	0.864	0.881	0.595

Source: Computed Data

All Cronbach's alpha and composite reliability values exceeded the 0.70 benchmark, and all AVE values exceeded 0.50, jointly supporting internal consistency and convergent validity across the five constructs (Fornell & Larcker, 1981). Discriminant validity was examined using the heterotrait - monotrait (HTMT) ratio of correlations, a method increasingly preferred over the traditional Fornell-Larcker criterion for its superior detection of validity violations (Henseler et al., 2015). As shown in Table 3, all HTMT values remained below the conservative 0.85 threshold, with the highest ratio observed between loyalty and retention (0.742)—an expected result given the conceptual proximity of these two constructs, but still comfortably within acceptable bounds.

Table 3. Discriminant Validity (HTMT Ratios)

	AIP	PV	CS	CL	CR
AIP	—				
PV	0.612	—			
CS	0.581	0.658	—		
CL	0.502	0.594	0.701	—	
CR	0.487	0.521	0.629	0.742	—

Source: Computed Data

Structural Model and Hypothesis Testing

Having established an acceptable measurement model, the structural model was estimated to test the six hypothesised paths. The structural model also demonstrated acceptable fit: χ^2 = 438.62, df = 203, CMIN/DF = 2.161, GFI = 0.911, AGFI = 0.889, CFI = 0.955, TLI = 0.948, RMSEA = 0.057, and SRMR = 0.045, indicating that the hypothesised structure was consistent with the observed data. All six hypothesised paths were statistically significant at the $p < .001$ level, as summarised in Table 4 and depicted in Figure 1.

Table 4. Structural Path Estimates and Hypothesis Testing

Hypothesis	Path	Standardized β	t-value	p-value	Result
H1	AIP → PV	0.52	8.94	< .001	Supported
H2	AIP → CS	0.31	5.27	< .001	Supported
H3	PV → CS	0.46	7.85	< .001	Supported
H4	CS → CL	0.58	9.41	< .001	Supported
H5	CS → CR	0.27	4.12	< .001	Supported
H6	CL → CR	0.49	7.66	< .001	Supported

Source: Primary Data

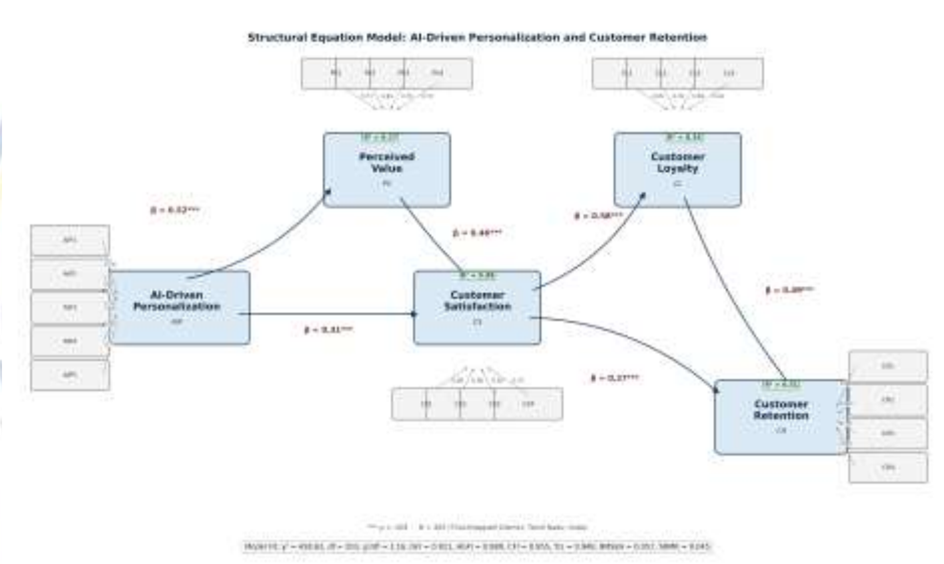
AI-driven personalization exerted the strongest effect on perceived value ($\beta = 0.52$), and a comparatively modest, though still significant, direct effect on satisfaction ($\beta = 0.31$). Perceived value itself contributed substantially to satisfaction ($\beta = 0.46$), suggesting that value perception functions as a meaningful conduit through which personalization's influence reaches satisfaction, rather than personalization acting on satisfaction in isolation. Satisfaction subsequently exerted the strongest single effect observed in the model on loyalty ($\beta = 0.58$), while its direct path to retention was the weakest of the six ($\beta = 0.27$)—loyalty's effect on retention ($\beta = 0.49$) was nearly double the magnitude of satisfaction's direct effect, implying that the loyalty-mediated route carries more weight in driving retention than the direct satisfaction route.

The model explained 27 percent of the variance in perceived value, 49 percent of the variance in satisfaction, 34 percent of the variance in loyalty, and 51 percent of the variance in retention. The relatively high R^2 for retention indicates that the hypothesised chain—personalization through value, satisfaction, and loyalty—captures a substantial portion of what drives continued patronage among the sampled shoppers, though, naturally, almost half of the variance remains attributable to factors outside this model, such as price competitiveness, delivery logistics, or habitual inertia, none of which were measured here.

Mediation Check

Given the sequential structure of the model, indirect effects were examined using bootstrapping with 5,000 resamples. The indirect effect of personalization on satisfaction through perceived value was significant ($\beta = 0.239$, $p < .001$), confirming partial mediation, since the direct path (H2) also remained significant. Similarly, the indirect effect of satisfaction on retention through loyalty was significant ($\beta = 0.284$, $p < .001$), again indicating partial rather than full mediation, as satisfaction's direct effect on retention (H5) persisted alongside the indirect route. This pattern—partial rather than full mediation at both junctures—suggests that personalization and satisfaction each retain some direct behavioural consequence that does not pass exclusively through the proposed intervening states.

Figure 1. Structural Equation Model of AI-Driven Personalization and Customer Retention



Discussion

The findings broadly support the sequential model proposed at the outset, though several details complicate a purely optimistic reading of AI-driven personalization's role in e-commerce. Personalization's effect on perceived value ($\beta = 0.52$) was considerably stronger than its direct effect on satisfaction ($\beta = 0.31$), which suggests that consumers in Tiruchirappalli district do not necessarily feel satisfied simply because a platform recognises their preferences; rather, they first register a practical benefit—reduced search time, better-fitting recommendations, perceived efficiency—and that benefit subsequently shapes how satisfied they feel. This sits comfortably alongside Lee and Cho's (2020) finding that personalization's value-enhancing function operates primarily through convenience rather than affect, though the present results extend that claim by showing the value-mediated pathway also feeds forward into loyalty and retention, not merely into a one-off satisfaction judgment.

A second pattern worth dwelling on concerns the relative strength of the loyalty-to-retention path ($\beta = 0.49$) against the direct satisfaction-to-retention path ($\beta = 0.27$). If satisfaction alone were sufficient to retain customers, the direct path would likely dominate; instead, the data suggest that attitudinal loyalty does meaningful additional work in converting satisfaction into actual retention behaviour. This aligns with Anderson and Srinivasan's (2003) argument that e-satisfaction is a necessary but insufficient condition for e-loyalty, and by extension, for retention—a satisfied customer who has not yet developed loyalty toward a specific platform may still be receptive to a competitor's offer, whereas a loyal customer has, in effect, raised their own switching threshold.

These results also speak to the scholarly tension flagged earlier regarding personalization's double-edged nature. Within this sample, no evidence emerged of personalization producing negative or non-significant effects; all paths were positive and significant. This does not, however, settle the debate raised by Aguirre et al. (2015) and others concerned about algorithmic intrusiveness. It may simply indicate that within Tiruchirappalli's e-commerce user base—where algorithmic curation, though increasingly common, has not yet reached the saturation levels seen in more digitally mature metros—consumers have not yet crossed the threshold at which personalization starts to feel like surveillance rather than service. Whether this finding would replicate in a market with higher digital fatigue is, frankly, an open question this single cross-sectional study cannot answer, and future longitudinal work would be needed to track whether the personalization-value relationship weakens as exposure accumulates.

It is also worth flagging a methodological caveat that bears on interpretation. The R^2 for satisfaction (0.49) is respectable but leaves roughly half the variance unexplained, hinting that constructs outside this model—price perception, trust in payment security, or delivery speed, none of which were captured here—likely play a comparable or even larger role in shaping satisfaction among this population. Readers should therefore treat the present model as a partial, rather than comprehensive, account of what drives retention in this market.

Managerial Implications

Several practical implications follow from these results, though e-commerce managers operating in semi-urban Indian markets should weigh them against local market conditions rather than treating them as universal prescriptions.

First, given that personalization's strongest pathway runs through perceived value rather than directly through satisfaction, firms investing in recommendation engines should prioritise features that visibly save customers time or effort—curated bundles, simplified comparison tools, or proactive restocking alerts—over features designed merely to demonstrate algorithmic sophistication. A recommendation system that feels clever but does not measurably reduce decision effort may underperform expectations.

Second, because loyalty carries more weight than direct satisfaction in driving retention, platforms should consider supplementing personalization efforts with loyalty-specific mechanisms—tiered membership programs, recognition of repeat patronage, or community-building features—rather than assuming that a satisfying transaction alone will secure repeat business. Satisfaction appears to be a necessary first step, but not a sufficient one, for the kind of behavioural lock-in that protects revenue against competitor promotions.

Third, the relatively modest direct effect of personalization on satisfaction (compared to its effect on value) implies that firms should resist over-investing in personalization at the expense of more fundamental service quality dimensions. A highly personalized experience built on top of unreliable delivery or poor customer service is unlikely to compensate for those deficiencies; personalization appears to amplify a generally positive experience rather than substitute for one.

Fourth, given that the sample skewed toward moderately frequent, digitally engaged shoppers, firms targeting less frequent or first-time online shoppers in similar Tier-II markets should be cautious about assuming the same psychological chain applies. Onboarding strategies for less experienced shoppers may need to establish basic trust and platform familiarity before personalization features can meaningfully influence value perception.

7. Conclusion

This study set out to examine how AI-driven personalization shapes customer retention in e-commerce, using perceived value, satisfaction, and loyalty as sequential mediating mechanisms, with data collected from 365 online shoppers across Tiruchirappalli district. The structural model, supported by acceptable measurement and structural fit indices, confirmed all six hypothesised paths, with personalization's influence reaching retention predominantly through value and loyalty rather than through a single direct route.

The contribution of this work lies less in demonstrating that personalization matters—that much is already assumed in industry practice—and more in clarifying how it matters, and through which intervening states its effects are most strongly transmitted. For scholars, the partial-mediation findings at both junctures suggest that future models of digital retention should resist collapsing personalization, value, satisfaction, and loyalty into a single composite predictor, since each construct appears to retain distinct explanatory power. For practitioners, the findings offer a more disciplined basis for allocating resources between personalization technology and complementary loyalty mechanisms, rather than treating algorithmic sophistication as a self-sufficient retention strategy.

Limitations and Directions for Future Research

This study is not without limitations. The cross-sectional design captures relationships at a single point in time and cannot establish causal direction with certainty; satisfaction and loyalty plausibly reinforce each other over repeated purchase cycles in ways a single-wave survey cannot detect. The sample, while adequate for SEM purposes, was drawn through convenience and snowball methods rather than probability sampling, limiting generalisability beyond the broad demographic profile captured here. Future research might usefully extend this model longitudinally, track the same respondents across multiple purchase cycles, or test whether the personalization-value relationship weakens once a threshold of algorithmic exposure is crossed—a question this study could identify but not resolve. Comparative studies across multiple Tier-II and Tier-III districts would also help determine whether the patterns observed here are specific to Tiruchirappalli or representative of semi-urban Indian e-commerce more broadly.

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