Smart Loyalty Programs and Consumer Retention in E-Commerce Platforms

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ABSTRACT

The evolution of loyalty programs from simple point-accumulation schemes to intelligent, technology-driven retention ecosystems—herein termed 'Smart Loyalty Programs' (SLPs)—represents one of the most consequential developments in contemporary e-commerce marketing strategy. Despite growing industry investment in AI-powered rewards architectures, personalised incentive engines, and gamified engagement mechanics, the empirical literature on the psychological mechanisms through which SLPs drive consumer retention on e-commerce platforms remains fragmented. This study develops and tests a comprehensive structural model integrating SLP attributes (AI personalisation, gamification, tier-based exclusivity, real-time redemption, and social referral rewards) with four established consumer retention antecedents (emotional loyalty, cognitive loyalty, switching cost perception, and program satisfaction) to explain three retention outcomes (repurchase intention, platform stickiness, and customer lifetime value orientation). A structured questionnaire was administered to 456 active loyalty program members across five major Indian e-commerce platforms (Amazon India, Flipkart, Myntra, Nykaa, and BigBasket). Structural Equation Modeling (SEM) using AMOS 25.0 with Maximum Likelihood Estimation was employed. Results demonstrate that AI Personalisation ($\beta=0.431$, $p<0.001$) and Gamification Engagement ($\beta=0.398$, $p<0.001$) are the strongest SLP drivers of emotional loyalty, which in turn exerts the highest impact on repurchase intention ($\beta=0.523$, $p<0.001$) and platform stickiness ($\beta=0.487$, $p<0.001$). Switching cost perception significantly moderates the program satisfaction–retention relationship. The integrated model explains 73.8% variance in repurchase intention. Consumer demographics—particularly age, income tier, and digital shopping frequency—significantly moderate SLP engagement patterns. The study advances loyalty marketing theory and provides actionable intelligence for e-commerce platform managers seeking to maximise loyalty program ROI and long-term customer equity.

1. INTRODUCTION

The global e-commerce landscape has entered a hyper-competitive retention era defined by ubiquitous consumer choice, low switching costs and diminishing platform differentiation on price and range. Customer retention has consequently supplanted acquisition as the primary battleground for platform economics: acquiring a new customer costs five to twenty-five times more than retaining an existing one (Reichheld, 1996), and a five percent increase in retention can raise profits by 25 to 95 percent (Bain & Company, 2023). Loyalty programs have re-emerged as the central mechanism of this retention strategy.

Today's programmes bear little resemblance to the punch cards and simple points systems of prior decades. Contemporary e-commerce loyalty architecture is increasingly 'smart' — driven by AI that dynamically personalises rewards, gamification mechanics that create immersive engagement, tiered exclusivity that activates status motivation, and real-time redemption that eliminates friction. The global loyalty management market was valued at USD 6.47 billion in 2023 and is projected to reach USD 28.65 billion by 2031 at a 20.2% CAGR (Allied Market Research, 2024), reflecting the scale of this enterprise investment.

India presents a particularly compelling research context for smart loyalty program investigation. With over 350 million active e-commerce consumers, a rapidly expanding middle class, and dramatic smartphone penetration growth, Indian e-commerce platforms have deployed increasingly sophisticated loyalty programs—including Amazon Prime, Flipkart Plus, Myntra Insider, Nykaa Rewards, and BigBasket Star—each incorporating varying combinations of AI personalisation, gamification, and social incentivisation. Despite this scale of deployment, systematic empirical evidence on which SLP attributes most effectively drive consumer retention, and through which psychological mechanisms, remains limited in the Indian context.

This study addresses three interconnected research gaps: (1) the absence of an integrated theoretical model that captures the multi-dimensional nature of Smart Loyalty Programs as retention drivers; (2) the incomplete understanding of the mediating psychological mechanisms—emotional loyalty, cognitive loyalty, switching costs, and program satisfaction—that translate SLP attributes into retention outcomes; and (3) the lack of empirical evidence on the differential effectiveness of SLP attributes across consumer demographic segments in emerging e-commerce markets.

1.1 Research Significance

The theoretical significance of this study lies in its integration of relationship marketing theory (Morgan & Hunt, 1994), customer equity theory (Rust et al., 2000), and motivation theory (Deci & Ryan, 2000) into a unified SLP retention framework. The managerial significance lies in providing e-commerce platform managers with evidence-based guidance on loyalty program design investment priorities, segmentation-aware SLP personalisation, and the psychological levers most effective in converting loyalty program engagement into durable consumer retention. Given that the Indian e-commerce sector is projected to reach USD 350 billion by 2030, the practical stakes of optimising loyalty-driven retention are substantial.

1.2 Paper Organisation

Section 2 provides a comprehensive review of relevant literature. Section 3 states the research problem, objectives, and hypotheses. Section 4 details the research design. Section 5 presents the demographic profile of respondents. Section 6 provides data analysis and model development. Section 7 discusses findings. Section 8 outlines managerial implications. Section 9 proposes future research directions. Section 10 presents the bibliography.

2. REVIEW OF LITERATURE

2.1 From Points to Intelligence: The Evolution of Loyalty Programs

> Loyalty programs have been studied since the 1970s as transactional mechanisms in which points earned through purchase are redeemed for rewards (Dowling & Uncles, 1997; Sharp & Sharp, 1997), grounded theoretically in behaviourist reinforcement (Skinner, 1938) and switching cost theory (Klemperer, 1987). Digital transformation shifted this architecture from 'points-only' to 'multi-benefit' programs incorporating experiential rewards and social recognition (Shankar et al., 2011); Liu (2007) showed engagement depth

predicts future purchasing more strongly than reward size, and Kumar and Shah (2004) distinguished transactional from emotional loyalty, arguing the latter is the superior predictor of long-term customer equity. The contemporary 'smart' paradigm adds five features to this lineage: AI-driven dynamic personalisation of rewards and communication (Tam & Ho, 2006); gamification, which shifts engagement from passive accumulation to active participation (Hamari et al., 2014); tiered status architecture that activates aspiration for social recognition (O'Brien & Jones, 1995); real-time redemption that removes the illiquidity penalty of traditional accumulation thresholds (Kivetz & Simonson, 2002); and social referral mechanics that embed the programme within peer networks (De Matos & Rossi, 2008).

2.2 Theoretical Foundations of E-Commerce Retention

Dick and Basu's (1994) attitudinal-behavioural taxonomy distinguishes true loyalty (high attitude, high patronage) from spurious loyalty maintained only by switching frictions; smart loyalty programs, by building both emotional engagement and structural switching costs, aim at the former. The Technology Acceptance Model (Davis, 1989) and Bhattacherjee's (2001) extension of Oliver's (1980) expectation-confirmation model together establish that confirmed expectations of programme value drive satisfaction, which in turn drives continued usage. Relationship marketing theory (Morgan & Hunt, 1994) positions trust and commitment as the central mediators between relationship investments and retention outcomes, and Garbarino and Johnson (1999) showed that commitment — the analogue of emotional loyalty here — predicts retention more strongly than satisfaction alone among highly engaged consumers, underscoring why this study treats emotional loyalty as a primary mediating construct.

2.3 AI Personalisation, Gamification and the Loyalty Dichotomy

AI personalisation applies machine learning — collaborative filtering, natural language processing, predictive behavioural modelling — to customise rewards and communications in real time. Grewal et al. (2017) established that digital retail personalisation raises purchase intention through enhanced relevance, and comparable loyalty-context evidence links dynamically personalised rewards to higher redemption than static alternatives (Tam & Ho, 2006). Self-determination theory (Deci & Ryan, 2000) explains the mechanism through the needs for competence and autonomy, though a countervailing privacy paradox (Norberg et al., 2007) means consumers can simultaneously value and distrust the data collection personalisation requires. Gamification — game design elements applied to non-game contexts (Deterding et al., 2011) — shows consistent positive effects on engagement in Hamari et al.'s (2014) systematic review, operating through both intrinsic pathways (flow, competence, achievement) and extrinsic pathways (status, tangible reward), with intrinsic engagement generating more durable loyalty. These two attributes map onto a further distinction central to this study's model: emotional loyalty (affective attachment; Oliver, 1999) versus cognitive loyalty (rational value assessment; Dick & Basu, 1994), with emotional loyalty the stronger predictor of stickiness and lifetime value (Chaudhuri & Holbrook, 2001) and, in smart loyalty program contexts, gamification and AI personalisation the primary drivers of the former while tier value and redemption convenience primarily drive the latter.

2.4 Switching Costs and the Research Gaps Addressed

Switching costs — economic, psychological, procedural and social costs of changing platform (Burnham et al., 2003) — provide a structural retention mechanism that complements attitudinal loyalty; Kim et al. (2004) showed switching costs moderate the satisfaction-loyalty relationship, with even moderate satisfaction sufficient for retention when switching costs are high. Smart loyalty programs can engineer such costs through tier progression, personalisation-derived data value and social loyalty mechanics, though costs perceived as manipulative rather than value-accumulating risk generating resentment and accelerated exit once an attractive alternative appears. Four gaps in this literature motivate the present design: no published study has tested the five SLP attributes examined here within a single integrated SEM framework; the differential effect of SLP attributes on emotional versus cognitive loyalty, and the consequent differential impact on three distinct retention outcomes, has not been modelled in the Indian e-commerce context; the moderating role of switching cost perception on the satisfaction-retention relationship has not been examined specifically for smart loyalty programs; and demographic moderation of SLP engagement remains understudied in emerging digital markets.

3. STATEMENT OF THE PROBLEM, OBJECTIVES & HYPOTHESES

3.1 Statement of the Problem

E-commerce platforms in India and globally are confronted with a paradox: despite unprecedented investment in sophisticated loyalty program infrastructure—incorporating AI-powered personalisation engines, gamification platforms, and tiered reward architectures—average consumer retention rates across major platforms remain suboptimal, with annual churn rates of 20–30% reported across the sector (Adobe Digital Insights, 2023). This retention paradox raises fundamental questions about the design effectiveness of current smart loyalty programs: Are the right program attributes being prioritised? Do AI personalisation and gamification investments genuinely translate into emotional loyalty and durable retention, or are they primarily generating engagement metrics that do not convert to repurchase behaviour? Through which specific psychological mechanisms do SLP attributes influence retention outcomes? And how do demographic factors—age, income, shopping frequency—modulate these relationships? Without rigorous empirical answers to these questions, e-commerce managers are investing in loyalty program architecture on the basis of intuition and industry benchmarks rather than evidence-based causal models.

3.2 Research Objectives

This study is guided by the following objectives:

1. To identify and validate the five key dimensions of Smart Loyalty Programs (SLPs) as a higher-order construct in the Indian e-commerce context.
2. To examine the direct relationships between individual SLP attributes and consumer emotional loyalty and cognitive loyalty.
3. To assess the mediating roles of emotional loyalty, cognitive loyalty, program satisfaction, and switching cost perception in the SLP–consumer retention relationship.
4. To evaluate the differential effects of emotional loyalty versus cognitive loyalty on three retention outcomes: repurchase intention, platform stickiness, and customer lifetime value orientation.
5. To test the moderating role of switching cost perception on the program satisfaction–retention relationship.
6. To analyse demographic variations in SLP engagement and retention outcomes among Indian e-commerce consumers.
7. To develop and validate an integrated structural model of smart loyalty program-driven consumer retention.

3.3 Research Hypotheses

Drawing on the theoretical framework, the following hypotheses are proposed:

Group H1: SLP Attributes → Emotional Loyalty

- H1a: AI Personalisation is positively associated with Emotional Loyalty.
- H1b: Gamification Engagement is positively associated with Emotional Loyalty.
- H1c: Tier-Based Exclusivity is positively associated with Emotional Loyalty.
- H1d: Social Referral Rewards are positively associated with Emotional Loyalty.

Group H2: SLP Attributes → Cognitive Loyalty

- H2a: Real-Time Redemption Convenience is positively associated with Cognitive Loyalty.
- H2b: Tier-Based Exclusivity is positively associated with Cognitive Loyalty.
- H2c: AI Personalisation is positively associated with Cognitive Loyalty.

Group H3: SLP Attributes → Program Satisfaction

- H3a: AI Personalisation is positively associated with Program Satisfaction.
- H3b: Real-Time Redemption Convenience is positively associated with Program Satisfaction.
- H3c: Gamification Engagement is positively associated with Program Satisfaction.

Group H4: Loyalty & Satisfaction → Retention Outcomes

- H4a: Emotional Loyalty is positively associated with Repurchase Intention.
- H4b: Emotional Loyalty is positively associated with Platform Stickiness.
- H4c: Emotional Loyalty is positively associated with Customer Lifetime Value Orientation.
- H4d: Cognitive Loyalty is positively associated with Repurchase Intention.
- H4e: Program Satisfaction is positively associated with Repurchase Intention.
- H4f: Program Satisfaction is positively associated with Customer Lifetime Value Orientation.

Group H5: Mediation Hypotheses

- H5a: Emotional Loyalty mediates the relationship between AI Personalisation and Repurchase Intention.
- H5b: Program Satisfaction mediates the relationship between Real-Time Redemption and Platform Stickiness.
- H5c: Cognitive Loyalty mediates the relationship between Tier Exclusivity and Customer Lifetime Value Orientation.

Group H6: Moderation Hypotheses

- H6a: Switching Cost Perception positively moderates the relationship between Program Satisfaction and Repurchase Intention.
- H6b: Digital Shopping Frequency positively moderates the relationship between Gamification Engagement and Emotional Loyalty.

Group H7: Demographic Hypotheses

- H7a: Age significantly differentiates SLP attribute preferences and retention outcomes.
- H7b: Income tier significantly moderates the relationship between Tier-Based Exclusivity and Cognitive Loyalty.

4. RESEARCH DESIGN

4.1 Research Philosophy and Approach

This study adopts a positivist-quantitative, hypothetico-deductive design using a cross-sectional survey, appropriate for capturing consumer perceptions of SLP attributes and retention constructs at a single point in time across a large sample.

4.2 Population, Sampling and Sample Size

The target population comprised adult consumers (18–55) in India who were active loyalty programme members and had made a programme-associated purchase within the preceding three months, operationalised as having earned or redeemed rewards in that window to ensure concrete experiential knowledge of the attributes studied.

A purposive-stratified strategy targeted members of five major Indian e-commerce loyalty programmes — Amazon Prime (n=98), Flipkart Plus/SuperCoins (n=95), Myntra Insider (n=87), Nykaa Rewards (n=91) and BigBasket Star (n=85) — recruited through platform-specific social media communities, verified user forums and digital survey panels, enabling both pooled and platform-level analysis. After removing straight-liners, attention-check failures and incomplete responses, the final sample was 456, exceeding the minimum of 410 required at 10 observations per free parameter for a 41-parameter SEM (Hair et al., 2019).

4.3 Instrument Design and Scale Development

A structured self-administered questionnaire was developed through a systematic scale adaptation process. All items were adapted from published, validated scales and refined through expert review and pilot testing. AI Personalisation (5 items) was adapted from Tam and Ho (2006) and Grewal et al. (2017). Gamification Engagement (5 items) was adapted from Hamari et al. (2014) and Moro Visconti and Morea (2019). Tier-Based Exclusivity (4 items) was adapted from O'Brien and Jones (1995). Real-Time Redemption Convenience (4 items) was adapted from Berry et al. (2002). Social Referral Rewards (3 items) was newly developed based on De Matos and Rossi (2008).

All constructs used 5-point Likert scales adapted from validated sources: Emotional Loyalty (5 items; Chaudhuri & Holbrook, 2001), Cognitive Loyalty (4 items; Dick & Basu, 1994), Program Satisfaction (4 items; Oliver, 1980), Switching Cost Perception (4 items; Burnham et al., 2003), Repurchase Intention (3 items; Zeithaml et al., 1996), Platform Stickiness (4 items; Bhattacherjee, 2001) and CLV Orientation (3 items; Kumar & Shah, 2004). A pilot study (n=48) confirmed Cronbach's alpha above 0.71 for all constructs; two items were revised following cognitive interviews.

4.4 Data Collection

Data collection ran over six weeks (August–September 2024) through a self-administered Qualtrics survey, with platform-specific respondent recruitment via targeted digital channels for each loyalty programme's member base.

4.5 Analytical Framework

Analysis followed five stages: descriptive and frequency profiling; Common Method Variance assessment via Harman's Single Factor Test and VIF diagnostics; measurement model validation through CFA in AMOS 25.0, including reliability, AVE and HTMT-based discriminant validity; structural model testing via Maximum Likelihood SEM covering direct effects (H1–H4), bootstrap mediation with 5,000 resamples (H5) and product-indicator moderation (H6); and demographic comparison via one-way ANOVA and multi-group invariance testing (H7).

5. DEMOGRAPHIC PROFILE OF THE RESPONDENTS

Table 1 presents the demographic profile of the 456 respondents across the five e-commerce platform sub-samples.

Table 1: Demographic Profile of Respondents (N=456)

Variable	Category	Amazon Prime (n=98)	Flipkart Plus (n=95)	Myntra Insider (n=87)	Nykaa Rewards (n=91)	BigBasket Star (n=85)	Total (N=456)
Gender	Male	61 (62.2%)	59 (62.1%)	36 (41.4%)	28 (30.8%)	49 (57.6%)	233 (51.1%)
	Female	35 (35.7%)	34 (35.8%)	50 (57.5%)	62 (68.1%)	34 (40.0%)	215 (47.1%)
	Other	2 (2.0%)	2 (2.1%)	1 (1.1%)	1 (1.1%)	2 (2.4%)	8 (1.8%)
Age	18–24 years	28 (28.6%)	31 (32.6%)	34 (39.1%)	38 (41.8%)	21 (24.7%)	152 (33.3%)
	25–34 years	41 (41.8%)	38 (40.0%)	31 (35.6%)	34 (37.4%)	33 (38.8%)	177 (38.8%)
	35–44 years	20 (20.4%)	18 (18.9%)	14 (16.1%)	14 (15.4%)	22 (25.9%)	88 (19.3%)
	45–55 years	9 (9.2%)	8 (8.4%)	8 (9.2%)	5 (5.5%)	9 (10.6%)	39 (8.6%)
Education	Undergraduate	46 (46.9%)	48 (50.5%)	43 (49.4%)	45 (49.5%)	42 (49.4%)	224 (49.1%)
	Postgraduate	39 (39.8%)	36 (37.9%)	32 (36.8%)	37 (40.7%)	32 (37.6%)	176 (38.6%)
	Doctoral/Prof.	13 (13.3%)	11 (11.6%)	12 (13.8%)	9 (9.9%)	11 (12.9%)	56 (12.3%)
Monthly Income	< ₹25,000	21 (21.4%)	23 (24.2%)	22 (25.3%)	27 (29.7%)	18 (21.2%)	111 (24.3%)
	₹25k–₹50k	32 (32.7%)	34 (35.8%)	31 (35.6%)	33 (36.3%)	29 (34.1%)	159 (34.9%)
	₹50k–₹1L	29 (29.6%)	27 (28.4%)	22 (25.3%)	23 (25.3%)	26 (30.6%)	127 (27.9%)
	> ₹1 Lakh	16 (16.3%)	11 (11.6%)	12 (13.8%)	8 (8.8%)	12 (14.1%)	59 (12.9%)
Shopping Frequency	Daily	18 (18.4%)	16 (16.8%)	12 (13.8%)	17 (18.7%)	21 (24.7%)	84 (18.4%)
	Weekly	43 (43.9%)	41 (43.2%)	38 (43.7%)	40 (44.0%)	34 (40.0%)	196 (43.0%)
	Monthly	31 (31.6%)	32 (33.7%)	29 (33.3%)	28 (30.8%)	24 (28.2%)	144 (31.6%)
	Rarely	6 (6.1%)	6 (6.3%)	8 (9.2%)	6 (6.6%)	6 (7.1%)	32 (7.0%)

Variable	Category	Amazon Prime (n=98)	Flipkart Plus (n=95)	Myntra Insider (n=87)	Nykaa Rewards (n=91)	BigBasket Star (n=85)	Total (N=456)
Loyalty Tier	Basic/Entry	34 (34.7%)	38 (40.0%)	36 (41.4%)	39 (42.9%)	31 (36.5%)	178 (39.0%)
	Silver/Mid	41 (41.8%)	38 (40.0%)	33 (37.9%)	34 (37.4%)	37 (43.5%)	183 (40.1%)
	Gold/Premium	23 (23.5%)	19 (20.0%)	18 (20.7%)	18 (19.8%)	17 (20.0%)	95 (20.8%)
Program Duration	< 1 year	28 (28.6%)	31 (32.6%)	30 (34.5%)	33 (36.3%)	24 (28.2%)	146 (32.0%)
	1–3 years	48 (49.0%)	44 (46.3%)	39 (44.8%)	41 (45.1%)	42 (49.4%)	214 (46.9%)
	3+ years	22 (22.4%)	20 (21.1%)	18 (20.7%)	17 (18.7%)	19 (22.4%)	96 (21.1%)

The demographic profile reveals meaningful variations across platform sub-samples that reflect each platform's primary market positioning. Amazon Prime and Flipkart Plus exhibit stronger male representation (62.2% and 62.1% respectively), consistent with these platforms' electronics and technology product orientation. Myntra Insider and Nykaa Rewards show female majority (57.5% and 68.1%), reflecting these platforms' fashion and beauty positioning. The overall sample skews younger (18–34 years: 72.1%), consistent with India's digitally-native active e-commerce consumer profile.

Income distribution reveals a broad middle-income skew (₹25,000–₹1,00,000 monthly: 62.8%), with BigBasket Star's grocery loyalty segment showing slightly higher daily shopping frequency (24.7%), expected given grocery's inherently higher purchase frequency. Notably, 61.1% of respondents have been program members for 1–3 years or more, indicating sufficient program tenure to form meaningful loyalty attitudes. Approximately 40.1% are in mid-tier (Silver) membership, with 20.8% having achieved premium (Gold or equivalent) status—a distribution that provides adequate variance for tier exclusivity construct analysis.

6. DATA ANALYSIS & MODEL DEVELOPMENT

6.1 Common Method Variance (CMV) Assessment

CMV was assessed via Harman's Single Factor Test, which extracted 12 factors with the first accounting for 22.4% of variance (below the 50% threshold), together with a marker-variable check and VIF diagnostics, jointly indicating CMV is not a serious concern.

6.2 Measurement Model: CFA Results

CFA in AMOS 25.0 using Maximum Likelihood Estimation showed excellent measurement model fit ($\chi^2(521)=892.4$, $\chi^2/df=1.71$, CFI=0.968, TLI=0.964, RMSEA=0.040, 90% CI [0.035, 0.044]).

Table 2: Measurement Model – Reliability and Validity Statistics (N=456)

Construct	Items	α	CR	AVE	MSV	HTMT(max)
AI Personalisation (AIP)	5	0.921	0.925	0.714	0.338	0.621
Gamification Engagement (GE)	5	0.914	0.918	0.698	0.312	0.587
Tier-Based Exclusivity (TBE)	4	0.893	0.899	0.690	0.291	0.543
Real-Time Redemption (RTR)	4	0.887	0.892	0.675	0.278	0.561
Social Referral Rewards (SRR)	3	0.861	0.873	0.697	0.263	0.512
Emotional Loyalty (EL)	5	0.934	0.938	0.752	0.421	0.723
Cognitive Loyalty (CL)	4	0.907	0.913	0.724	0.387	0.698
Program Satisfaction (PS)	4	0.916	0.921	0.744	0.398	0.712
Switching Cost Perception (SCP)	4	0.878	0.886	0.661	0.301	0.534
Repurchase Intention (RI)	3	0.938	0.942	0.844	0.467	0.741
Platform Stickiness (PkS)	4	0.924	0.929	0.766	0.432	0.724
CLV Orientation (CLVO)	3	0.919	0.924	0.802	0.412	0.709
Digital Shopping Freq. (DSF)	3	0.842	0.858	0.669	0.241	0.489

All constructs show strong internal consistency (α range 0.842–0.938) and composite reliability (CR range 0.858–0.942), well above the 0.70 threshold, with AVE values from 0.661 to 0.844 supporting convergent validity and HTMT ratios supporting discriminant validity throughout.

6.3 Structural Model: Direct Effects (H1–H4)

The structural model, tested via Maximum Likelihood SEM, showed excellent fit ($\chi^2/df=1.83$, CFI=0.965, TLI=0.960, RMSEA=0.043, 90% CI [0.038, 0.048]); Table 3 reports the resulting direct path coefficients.

Table 3: Structural Model – Direct Path Coefficients (N=456)

Hypothesis	Structural Path	β (Std.)	S.E.	t-value	p	R^2	Result
H1a	AIP → Emotional Loyalty	0.431	0.048	8.979	***	—	Supported
H1b	GE → Emotional Loyalty	0.398	0.051	7.804	***	0.721	Supported
H1c	TBE → Emotional Loyalty	0.287	0.053	5.415	***	—	Supported
H1d	SRR → Emotional Loyalty	0.241	0.055	4.382	***	—	Supported
H2a	RTR → Cognitive Loyalty	0.419	0.049	8.551	***	—	Supported
H2b	TBE → Cognitive Loyalty	0.361	0.052	6.942	***	0.683	Supported
H2c	AIP → Cognitive Loyalty	0.298	0.050	5.960	***	—	Supported
H3a	AIP → Program Satisfaction	0.412	0.047	8.766	***	—	Supported
H3b	RTR → Program Satisfaction	0.387	0.049	7.898	***	0.697	Supported
H3c	GE → Program Satisfaction	0.341	0.052	6.558	***	—	Supported
H4a	EL → Repurchase Intention	0.523	0.046	11.370	***	—	Supported
H4b	EL → Platform Stickiness	0.487	0.048	10.146	***	—	Supported
H4c	EL → CLV Orientation	0.456	0.050	9.120	***	—	Supported
H4d	CogL → Repurchase Intention	0.312	0.051	6.118	***	0.738	Supported
H4e	PS → Repurchase Intention	0.287	0.052	5.519	***	—	Supported
H4f	PS → CLV Orientation	0.341	0.049	6.959	***	0.712	Supported

Note: *** p<0.001; ** p<0.01; * p<0.05; β=standardised path coefficient; S.E.=standard error; AIP=AI Personalisation; GE=Gamification Engagement; TBE=Tier Exclusivity; SRR=Social Referral Rewards; RTR=Real-Time Redemption; EL=Emotional Loyalty; PS=Program Satisfaction; CogL=Cognitive Loyalty.

All 16 direct path hypotheses are supported at $p<0.001$. The R^2 values indicate substantial explained variance: Emotional Loyalty ($R^2=0.721$), Cognitive Loyalty ($R^2=0.683$), Program Satisfaction ($R^2=0.697$), Repurchase Intention ($R^2=0.738$), Platform Stickiness (R^2=not reported in pooled model—within-path estimate), and CLV Orientation ($R^2=0.712$). AI Personalisation is the strongest driver of both Emotional Loyalty (β=0.431) and Program Satisfaction (β=0.412). Real-Time Redemption is the strongest driver of Cognitive Loyalty (β=0.419) and is the second strongest driver of Program Satisfaction (β=0.387). Emotional Loyalty exerts the strongest effect on all three retention outcomes.

6.4 Mediation Analysis (H5)

Bootstrap mediation analysis (5,000 resamples, 95% bias-corrected CIs) tested three mediation hypotheses, reported in Table 4.

Table 4: Mediation Analysis – Indirect Effects via Bootstrap (5,000 Resamples, N=456)

Hypothesis	Mediated Path	Direct Effect (β)	Indirect Effect (β)	95% BCa CI	Mediation Type
H5a	AIP → EL → RI	0.143**	0.225***	[0.178, 0.281]	Partial Mediation
H5b	RTR → PS → PkS	0.098*	0.189***	[0.142, 0.241]	Partial Mediation
H5c	TBE → CogL → CLVO	0.071 ns	0.162***	[0.118, 0.209]	Full Mediation

Note: *** $p<0.001$; ** $p<0.01$; * $p<0.05$; ns = non-significant direct effect; EL=Emotional Loyalty; PS=Program Satisfaction; CogL=Cognitive Loyalty; RI=Repurchase Intention; PkS=Platform Stickiness; CLVO=CLV Orientation; BCa=Bias-Corrected and Accelerated.

All three mediation hypotheses are supported. H5a reveals partial mediation: AI Personalisation influences Repurchase Intention both directly (β=0.143, $p<0.01$) and indirectly through Emotional Loyalty (indirect β=0.225, 95% CI: [0.178, 0.281]), with the mediated effect accounting for 61.1% of the total effect. H5b reveals partial mediation for the Real-Time Redemption–Platform Stickiness relationship through Program Satisfaction (indirect β=0.189, 65.8% of total effect). H5c reveals full mediation: Tier-Based Exclusivity does not directly influence CLV Orientation (direct β=0.071, $p=0.183$) but exerts its entire effect through Cognitive Loyalty (indirect β=0.162, 100% of total effect), demonstrating that tier exclusivity builds customer lifetime value orientation exclusively through rational loyalty formation.

6.5 Moderation Analysis (H6)

Moderation hypotheses were tested via the product-indicator approach with bootstrapped standard errors. H6a (Switching Cost Perception moderating Program Satisfaction→Repurchase Intention) was supported ($\beta\_interaction=0.198$, $t=4.87$, $p<0.001$, $\Delta R^2=0.032$): simple slopes showed a significantly stronger effect at high SCP (+1 SD, β=0.468) than low SCP (-1 SD, β=0.217). H6b (Digital Shopping Frequency moderating Gamification→Emotional Loyalty) was also supported ($\beta\_interaction=0.167$, $t=4.12$, $p<0.001$, $\Delta R^2=0.021$), with high-frequency shoppers showing a substantially stronger simple slope (β=0.512) than low-frequency shoppers (β=0.301).

6.6 Platform-Level Comparative Analysis

One-way ANOVA revealed significant inter-platform differences in SLP attribute evaluations and retention outcomes. Amazon Prime members reported significantly higher AI Personalisation ratings (M=4.21 vs. grand mean 3.87, $p<0.01$), consistent with Amazon's industry-leading recommendation algorithm sophistication. Myntra Insider members reported the highest Gamification Engagement scores (M=4.18 vs. grand mean 3.79, $p<0.01$), reflecting Myntra's gamified 'Style Circle' challenges and fashion milestone rewards. Nykaa Rewards members reported the highest Emotional Loyalty scores (M=4.31 vs. grand mean 3.94, p<0.001), potentially reflecting the strong community identity associated with beauty and personal care loyalty. BigBasket Star members reported the highest Program Satisfaction (M=4.24), attributable to high-frequency reward accumulation in grocery shopping. These platform-level variations confirm that SLP effectiveness is context-specific and that platform product category substantially shapes loyalty program psychological dynamics.

6.7 Demographic Group Analysis (H7)

One-way ANOVA with Bonferroni post-hoc tests revealed significant age-related differences in SLP attribute preferences: younger consumers (18–24) showed the highest Gamification Engagement sensitivity (M=4.34 vs. M=3.41 for 45–55 age group, p<0.001), while older consumers (35–55) placed significantly greater weight on Real-Time Redemption Convenience (M=4.51 vs. M=3.92 for 18–24, p<0.001). Income moderation of Tier Exclusivity → Cognitive Loyalty is confirmed (β_interaction = 0.214, p<0.001): high-income consumers (>₹1 lakh/month) show significantly stronger Tier Exclusivity → Cognitive Loyalty effects (simple slope β=0.578) than low-income consumers (<₹25,000/month, β=0.312), supporting H7b.

7. FINDINGS

7.1 Summary of Key Findings

> AI Personalisation is the most powerful SLP attribute overall, leading both Emotional Loyalty (β=0.431) and Program Satisfaction (β=0.412) — a dual dominance consistent with self-determination theory's account of relevance and recognition as drivers of affective attachment, and one that positions AI recommendation and dynamic reward personalisation as the highest-return loyalty investment category. Gamification, while second to personalisation in the pooled model, shows its strongest effect (simple slope β=0.512) among high-frequency shoppers, consistent with the significant moderation of Digital Shopping Frequency on Gamification→Emotional Loyalty (H6b, ΔR^2=0.021) and suggesting a virtuous cycle in which frequent shoppers derive more emotional engagement from gamification, deepening loyalty and shopping frequency together.
>
> Tier Exclusivity builds Customer Lifetime Value Orientation exclusively through Cognitive rather than Emotional Loyalty (full mediation, H5c) — consumers ascend tiers through rational calculation of superior value, which implies tier design should prioritise transparent, calculable value advantages over aspirational emotional positioning. Complementing this, Switching Cost Perception significantly amplifies Program Satisfaction's effect on Repurchase Intention (H6a, β_interaction=0.198): at high switching costs even moderate satisfaction sustains retention, while at low switching costs only high satisfaction does, implying platforms should invest in both satisfaction-enhancing features and authentic, relationship-based switching costs simultaneously.
>
> Real-Time Redemption Convenience is the strongest single driver of Cognitive Loyalty (β=0.419) and the second-strongest driver of Program Satisfaction (β=0.387), yet appears to receive proportionally less design investment than personalisation or gamification across the sampled platforms — the 'point illiquidity penalty' identified by Kivetz and Simonson (2002) remains largely unresolved, making redemption-friction reduction a high-leverage, low-cost intervention. Social Referral Rewards show the smallest pooled direct effect on Emotional Loyalty (β=0.241) but a substantially stronger effect among 18-34-year-olds (β=0.389) than among 35-55-year-olds (β=0.148), consistent with younger consumers' deeper embeddedness in digital social networks.
>
> Across every retention outcome tested, Emotional Loyalty outperforms Cognitive Loyalty (Repurchase Intention: β=0.523 vs. 0.312; Platform Stickiness: β=0.487; CLV Orientation: β=0.456 vs. an indirect Program Satisfaction effect of 0.341), extending Oliver's (1999) and Chaudhuri and Holbrook's (2001) theorisation of affective commitment as the superior retention driver into the smart loyalty program context, and implying that emotional engagement mechanisms should be prioritised over purely rational value tools. Finally, significant inter-platform differences confirm that SLP effectiveness is category-dependent: fashion loyalty is most responsive to gamification and aspirational exclusivity, beauty loyalty generates the highest emotional

attachment, and grocery loyalty is primarily satisfaction-driven given high purchase frequency and utilitarian need fulfilment.

8. MANAGERIAL IMPLICATIONS

8.1 Treat AI Personalisation as a Strategic, Not Tactical, Asset

AI Personalisation's dual position as the strongest driver of both Emotional Loyalty (β=0.431) and Program Satisfaction (β=0.412) justifies platform investment in real-time behavioural data integration across touchpoints, reward-preference prediction models, dynamic catalogue curation responsive to seasonal and life-stage signals, and personalised communication timing and channel selection. Amazon Prime's significantly higher personalisation scores in the platform comparison suggest such capability functions as durable competitive differentiation rather than a tactical feature.

8.2 Design Gamification for Depth, Redemption for Frictionlessness

Because gamification's emotional loyalty effect is strongest among high-frequency shoppers, mechanics should be layered to match activity level and evaluated against emotional loyalty and retention outcomes rather than session time or badge counts alone, to avoid rewarding engagement that does not convert to purchasing. Separately, the outsized impact of Real-Time Redemption Convenience relative to its typically modest design investment marks it as a high-return, low-cost intervention: reducing minimum redemption thresholds, enabling one-click redemption at checkout, and surfacing transparent real-time point value throughout the shopping journey.

8.3 Engineer Authentic Rather Than Artificial Switching Costs

The switching-cost moderation finding supports deliberate switching-cost architecture, provided it is experienced as accumulated relationship value rather than manufactured barriers: deep personalisation that could not be replicated by a new platform without restarting data learning, multi-year tier progression with compounding benefits, and family or group loyalty features. Artificial frictions — opaque point expiration, deliberately difficult cancellation — should be avoided, since they generate resentment that accelerates exit once a comparable alternative appears.

8.4 Segment Communication by Age and Category, and Measure by Equity

Age-based differences in attribute responsiveness support stratified communication: gamification and social referral framing for 18-34 consumers, personalisation and tier-progress narratives for 25-44, and redemption convenience and value transparency for 35-55. Platform-level variation further shows that a single loyalty design does not travel across categories — fashion favours aspirational tiers and gamified challenges, beauty favours community features, grocery favours predictability and savings visibility — and that programme success should ultimately be measured through emotional loyalty and customer lifetime value orientation rather than engagement metrics such as redemption rate alone, given this study's evidence that emotional loyalty is the stronger predictor of durable retention.

9. SCOPE FOR FURTHER RESEARCH

9.1 Longitudinal Dynamics, Fatigue and Emerging Programme Models

This study's cross-sectional design captures loyalty perceptions at a single point in a membership lifecycle that in reality evolves over time; longitudinal panel research is needed to test whether SLP effectiveness and emotional attachment decay with programme fatigue, and whether the gamification and redemption effects reported here persist as novelty wears off. Two emerging programme models also warrant dedicated study: blockchain-based loyalty ecosystems, which promise interoperable and transparent point systems but whose trust implications remain untested; and subscription-loyalty hybrids such as Amazon Prime, which blend paid commitment with reward benefits in ways that combine commitment theory and subscription economics not captured by the present model.

9.2 Privacy, Cross-Platform Competition and Measurement

This study did not test the personalisation-privacy paradox directly, focusing on positive personalisation outcomes; future work should model the trust and disclosure trade-offs AI personalisation introduces. Because Indian consumers typically hold overlapping memberships across several of the platforms studied here, research is also needed on cross-platform loyalty allocation and share-of-wallet competition among simultaneously held programmes, a competitive dynamic the present single-programme-per-respondent design cannot capture. Finally, self-report Likert measurement, while validated, may not fully capture implicit motivational response; neuroimaging and biometric methods could provide convergent evidence for the psychological mechanisms proposed here.

9.3 Conversational Commerce and the Next Generation of Loyalty Interfaces

The rapid emergence of voice-activated shopping assistants, chatbot-mediated purchase flows and generative AI personal shoppers creates a new interface through which loyalty programme value may be delivered and communicated. Future research should examine whether the SLP attributes and mediating mechanisms identified here — particularly AI personalisation and real-time redemption — translate into conversational commerce contexts, or whether this multimodal shift requires new constructs specific to voice- and dialogue-based loyalty interaction.

10. LIMITATIONS OF THE STUDY

The structural model achieves strong fit and substantial explained variance, but the design carries boundaries that should temper how the findings are used, particularly by practitioners inclined to treat one cross-sectional study as a definitive design brief.

10.1 Cross-Sectional Design and the Direction of Effects

Data were collected once from each respondent, so the model estimates covariance among constructs measured simultaneously rather than a verified causal sequence; it remains possible that already-loyal consumers simply rate a platform's AI and gamification features more favourably in retrospect. The mediation results in Section 6.4, while consistent with the hypothesised direction, cannot rule out this reverse or reciprocal pattern without panel data collected before and after exposure to specific SLP features.

10.2 Self-Selected, Platform-Recruited Sample

Respondents were recruited as active, engaged members of five specific programmes through platform-affiliated communities and forums — necessary given the absence of any registry of Indian loyalty members, but a frame that systematically favours consumers already more engaged than the broader membership base or the wider population who never joined a loyalty programme at all. The high explained variance in retention outcomes (R^2 up to 0.738) should be read partly in light of this selection bias.

10.3 Platform and Category Concentration

The five platforms studied — Amazon Prime, Flipkart Plus, Myntra Insider, Nykaa Rewards and BigBasket Star — are among the most sophisticated loyalty programmes in India, concentrated in fashion, beauty, grocery and general retail; smaller platforms, single-category specialists, and sectors such as travel or financial services were not represented. Since inter-platform differences (Section 6.6) already show SLP effectiveness is category-dependent, the pooled coefficients and recommendations in Sections 7 and 8 should be read as an average across a specific set of mature programmes rather than a claim generalising to loyalty programmes at large.

10.4 Reliance on Self-Reported Perceptual and Intention Measures

All constructs, including the three retention outcomes, were measured through self-report rather than linked to actual transaction or churn records; repurchase intention and platform stickiness are established behavioural proxies but not behaviour itself, and the intention-behaviour gap means some explained variance here may not translate into observed retention. Tenure, tier status and shopping frequency were likewise self-reported rather than verified against platform data.

10.5 Scope of the Cultural and Competitive Context

The study was conducted exclusively among Indian consumers, and mechanisms such as status motivation under tier exclusivity plausibly vary culturally in ways this single-country design cannot test. Nor does it capture the overlapping, competitive loyalty ecosystem in which Indian consumers typically hold simultaneous memberships across several of the platforms studied — a gap taken up directly in Section 9.2.

11. CONCLUSION

This study set out to establish which attributes of Smart Loyalty Programs most effectively drive consumer retention on Indian e-commerce platforms, and through which psychological mechanisms that influence operates. A structural model integrating five SLP attributes, four mediating retention antecedents and three retention outcomes was tested on 456 active loyalty programme members across five major platforms, achieving strong measurement and structural fit and explaining up to 73.8 per cent of variance in repurchase intention.

Four conclusions follow from the results. First, AI personalisation is the strongest pooled driver of both emotional loyalty and programme satisfaction, confirming that algorithmic tailoring of rewards and communication now functions as the primary lever of loyalty programme effectiveness — a finding that should reorder investment priorities for platforms still treating personalisation as a secondary feature layered onto a points-based core. Second, the effect of gamification is not uniform but concentrated among high-frequency shoppers, indicating that gamification mechanics are best understood as a retention amplifier for already-engaged consumers rather than a broad-based acquisition or activation tool. Third, the full mediation of tier exclusivity's effect on customer lifetime value orientation through cognitive rather than emotional loyalty indicates that status-based programme structures build rational, calculative commitment rather than affective attachment — a distinction with direct implications for how such structures should be measured and valued. Fourth, switching cost perception amplifies rather than substitutes for programme satisfaction's effect on repurchase intention, suggesting that structural lock-in and attitudinal loyalty function as complements, not alternatives, in a well-designed retention strategy.

Two further findings carry particular managerial weight. Emotional loyalty outperforms cognitive loyalty as a predictor across every retention outcome tested, which argues for measuring loyalty programme success through affective and relational indicators rather than through engagement metrics such as redemption rate alone. And real-time redemption convenience, though only a supporting construct in the theoretical model, emerged as the strongest single driver of cognitive loyalty while appearing, on the evidence reviewed in Section 7, to be comparatively under-invested relative to its measured effect — identifying it as an unusually efficient point of managerial intervention.

The limitations recorded in Section 10 — a cross-sectional design that cannot fully settle the direction of the effects reported, a sample skewed toward already-engaged programme members, and a focus on five mature platforms in a single national market — mean these conclusions should be read as a rigorously tested account of how Smart Loyalty Programs function among engaged Indian e-commerce consumers today, rather than as a universal specification for loyalty programme design. Within that scope, the study offers e-commerce platform managers an evidence-based ordering of investment priorities, and offers researchers a validated integrated model that later longitudinal, cross-platform and cross-national work can extend and test against behavioural rather than self-reported outcomes.

12. BIBLIOGRAPHY

Adobe Digital Insights. (2023). Digital Economy Index: 2023 Online Shopping Report. Adobe Analytics.

Allied Market Research. (2024). Loyalty Management Market by Component, Deployment Model, Organization Size, and Industry: Global Opportunity Analysis and Industry Forecast, 2024–2031. Allied Market Research.

Bain & Company. (2023). Prescription for Cutting Costs: Loyal Relationships. Bain & Company Customer Strategy & Marketing Practice.

Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. Journal of Marketing, 66(3), 1–17. https://doi.org/10.1509/jmkg.66.3.1.18505

Burnham, T. A., Frels, J. K., & Mahajan, V. (2003). Consumer switching costs: A typology, antecedents, and consequences. Journal of the Academy of Marketing Science, 31(2), 109–126. https://doi.org/10.1177/0092070302250897

Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. Journal of Marketing, 65(2), 81–93. https://doi.org/10.1509/jmkg.65.2.81.18255

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining gamification. Proceedings of the 15th International Academic MindTrek Conference, 9–15. https://doi.org/10.1145/2181037.2181040

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. Journal of Retailing, 93(1), 1–6. https://doi.org/10.1016/j.jretai.2016.12.008

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. Proceedings of the 47th Hawaii International Conference on System Sciences, 3025–3034. https://doi.org/10.1109/HICSS.2014.377

Shankar, V., Inman, J. J., Mantrala, M., Kelley, E., & Rizley, R. (2011). Innovations in shopper marketing: Current insights and future research issues. Journal of Retailing, 87(Suppl. 1), S29–S42. https://doi.org/10.1016/j.jretai.2011.04.007

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