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Role of AI-Based Personalization in Enhancing Consumer Confidence and Purchase Decisions

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ABSTRACT

AI-based personalization has transitioned from a competitive differentiator to a baseline operational expectation in digital commerce, yet the precise cognitive and affective mechanisms through which personalization shapes consumer confidence and the quality of purchase decisions remain theoretically fragmented and empirically underexplored. This study advances a novel integrated framework—rooted in the Elaboration Likelihood Model (ELM), the Stimulus-Organism-Response (S-O-R) paradigm, and Trust Transfer Theory—to explain how five AI personalization stimuli (predictive recommendation fit, dynamic pricing personalisation, personalised search ranking, adaptive push notification timing, and AI-driven post-purchase follow-up) influence two cognitive-affective organism states (consumer confidence and perceived personalisation quality) that drive three purchase decision outcomes (purchase decision quality, decision regret minimisation, and repeat purchase commitment). Trust Transfer—the process by which trust in AI technology transfers to trust in the platform vendor—is hypothesised as a pivotal mediator, while AI literacy and involvement level are tested as moderators within the ELM framework. A structured questionnaire was administered to 468 consumers of five major Indian digital service platforms (Swiggy, Zomato, BookMyShow, MakeMyTrip, and Practo). Structural Equation Modeling (SEM) using AMOS 27.0 with Maximum Likelihood Estimation confirmed excellent model fit. Predictive Recommendation Fit ($\beta = 0.462$, $p < 0.001$) and Adaptive Push Notification Timing ($\beta = 0.318$, $p < 0.001$) are the strongest confidence drivers. Trust Transfer significantly mediates the consumer confidence–purchase decision quality relationship (indirect $\beta = 0.287$, 95% BCa CI: [0.231, 0.348]). AI Literacy moderates the personalization–confidence relationship such that high-literacy consumers form confidence through central route processing while low-literacy consumers rely on peripheral cues. The model explains 71.8% variance in Purchase Decision Quality and 68.4% in Repeat Purchase Commitment. Findings advance ELM application to AI commerce and provide nuanced design and communication prescriptions for AI-powered service platforms.

Keywords: AI Personalization; Consumer Confidence; Purchase Decision Quality; Elaboration Likelihood Model; Trust Transfer; S-O-R Framework; Perceived Personalisation Fit; Decision Regret; SEM; Digital Service Platforms; India

1. INTRODUCTION

The contemporary digital consumer inhabits a world of algorithmically curated choices. Every product surfaced, notification dispatched, search result ordered, and follow-up message timed is the output of AI systems that have modelled the individual consumer in granular detail—processing purchase histories, browsing sequences, device contexts, temporal patterns, and social signals to construct a probabilistic model of what that specific consumer wants, when they want it, and how best to present it. This artificial intelligence-mediated personalisation infrastructure has become the operational backbone of the world's most successful digital commerce platforms. Amazon's recommendation engine alone reportedly drives 35% of its total revenue; Netflix's personalisation system is estimated to save the company $1 billion annually in customer retention (Gomez-Uribe & Hunt, 2015). In India, Swiggy's AI-powered personalised restaurant feeds, Zomato's predictive reorder suggestions, MakeMyTrip's dynamic personalised itinerary offers, and Practo's AI-matched doctor recommendations are reshaping the consumer's experience of digital service discovery and selection.

Yet as AI personalization becomes more pervasive and more powerful, a fundamental consumer psychology question demands attention: does AI personalization genuinely enhance the quality of consumer purchase decisions—helping people make choices they are more satisfied with, less likely to regret, and more motivated to repeat—or does it primarily accelerate impulsive decisions that consumers would have made anyway? This distinction between decision confidence (the subjective sense of certainty) and decision quality (the objective goodness of the choice, reflected in post-purchase satisfaction and absence of regret) is central to this study. It is entirely possible for AI personalization to inflate decision confidence while simultaneously degrading decision quality—for instance, by presenting only choices that match existing preferences while suppressing alternatives that might better serve unexpressed consumer needs.

This study adopts a novel theoretical framework that integrates three complementary perspectives. The Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986) provides the cognitive processing architecture: consumers with high AI literacy and high involvement process AI personalization cues through the central route (careful evaluation of personalisation accuracy and relevance), while low literacy/low involvement consumers rely on peripheral cues (interface aesthetics, notification styling, social proof signals). The S-O-R framework (Mehrabian & Russell, 1974) provides the stimulus-response architecture: AI personalization stimuli trigger internal organism states (consumer confidence, perceived personalisation quality) that drive behavioural responses (purchase decision quality, repeat commitment). Trust Transfer Theory (McKnight & Chervany, 2002; Stewart, 2003) provides the mechanism through which trust in the AI personalization system transfers to trust in the platform vendor, amplifying the confidence-to-purchase conversion pathway.

The Indian digital service platform context offers compelling empirical grounding for this investigation. India's digital service economy—encompassing food delivery, travel booking, entertainment, and health services—processes over 14 million AI-personalised transactions daily across the five platforms included in this study. Indian consumers simultaneously exhibit high AI feature engagement and persistent ambivalence about AI-driven recommendations, creating a nuanced research environment that is more theoretically generative than the uniformly high-acceptance contexts of Western markets.

1.1 Theoretical Contributions

This study makes three distinct theoretical contributions. First, it provides the first empirical application of ELM to AI personalization effects on purchase decision quality (as opposed to mere purchase intention), with AI literacy as the cognitive elaboration moderator. Second, it introduces Trust Transfer as a mediating mechanism in the AI personalization-to-purchase quality pathway, extending Stewart's (2003) inter-entity trust transfer model to the AI-platform vendor dyad. Third, it distinguishes between decision confidence (subjective) and decision quality (objective-proxied) as separate outcomes, with different AI personalisation dimension predictors—addressing a critical gap in existing literature that conflates these conceptually distinct outcomes.

1.2 Paper Structure

Section 2 reviews the theoretical and empirical literature. Section 3 presents the research problem, objectives, and hypotheses. Section 4 describes the research design. Section 5 profiles the respondent sample. Section 6 presents data analysis and model results. Section 7 discusses key findings. Section 8 elaborates managerial implications. Section 9 proposes future research directions. Section 10 provides the bibliography.

2. REVIEW OF LITERATURE

2.1 AI-Based Personalization in Digital Service Platforms

AI-based personalization in digital service platforms extends beyond product recommendation to encompass the complete orchestration of the individual consumer's service encounter. Shankar et al. (2021) defined AI-driven service personalisation as 'the application of machine learning, deep learning, and natural language processing to dynamically configure service delivery parameters—including option presentation, pricing, communication sequencing, and interface layout—in real time according to inferred individual consumer states and trajectories.' This definition foregrounds five operationally distinct personalisation dimensions that form this study's stimulus constructs.

Predictive Recommendation Fit (PRF) refers to the alignment between AI-generated service recommendations and the consumer's expressed and latent preferences—operationalised as the consumer's subjective assessment that 'these suggestions really understand what I want' (Jiang & Benbasat, 2007; Covington et al., 2016). Dynamic Pricing Personalisation (DPP) refers to AI-generated individualised price offers, discounts, and bundle configurations calibrated to a consumer's price sensitivity profile and purchase probability (Grewal et al., 2011). Personalised Search Ranking (PSR) refers to the reordering of search results, restaurant listings, doctor profiles, or travel options based on AI-inferred individual preference weights (Pan et al., 2019). Adaptive Push Notification Timing (APNT) refers to AI-driven delivery of notifications at the individual's moment of highest receptivity, optimised through reinforcement learning on response patterns (Sahoo et al., 2022). AI-Driven Post-Purchase Follow-Up (APPF) refers to personalised post-transaction communication—review prompts, reorder suggestions, complementary service recommendations—delivered at AI-predicted optimal intervals post-purchase (Kumar et al., 2019).

2.2 Elaboration Likelihood Model: Application to AI Personalization

The Elaboration Likelihood Model (Petty & Cacioppo, 1986) posits two routes to attitude change and decision formation: the central route, characterized by high cognitive elaboration (careful scrutiny of argument quality and information accuracy); and the peripheral route, characterised by low elaboration reliance on heuristic cues (source attractiveness, interface aesthetics, social proof). ELM's applicability to digital commerce persuasion has been established across multiple contexts (Petty & Wegener, 1999; Bhattacherjee & Sanford, 2006), but its application to AI personalization remains nascent.

This study extends ELM to the AI personalization context by proposing that AI Literacy (consumers' knowledge and understanding of how AI systems work) and Purchase Involvement (the perceived importance of getting the purchase decision right) jointly determine the processing route through which AI personalisation influences consumer confidence and decision quality. High-literacy, high-involvement consumers process AI personalisation through the central route—evaluating the accuracy of recommendations, the fairness of personalised pricing, and the relevance of search rankings with cognitive rigour. These consumers form confidence that is grounded in verified AI accuracy, making their confidence-to-decision quality conversion more reliable. Low-literacy, low-involvement consumers process personalisation through peripheral cues—inferring AI competence from interface polish, notification frequency, and social proof elements—forming confidence that may be less calibrated to actual personalisation accuracy.

2.3 S-O-R Framework in Digital Commerce

The Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974), originating in environmental psychology, has been widely adapted to digital commerce contexts. The framework posits that environmental stimuli trigger internal cognitive and affective organism states that drive approach or avoidance behavioural responses. In e-commerce applications, stimuli typically include website design cues (Parboteeah et al., 2009), social commerce features (Zhang et al., 2014), and service quality signals (Blut et al., 2021). In this study, the five AI personalization dimensions constitute the stimuli, consumer confidence and perceived personalisation quality are the organism states, and purchase decision quality, decision regret minimisation, and repeat purchase commitment are the responses.

The S-O-R framework's strength in this context lies in its ability to explain both immediate behavioural responses (purchase decision quality within the current transaction) and extended behavioural responses (repeat purchase commitment across future transactions), with the organism states as the psychological infrastructure that bridges stimuli to both response types. Chang and Chen (2008) applied S-O-R to e-commerce website quality, demonstrating that design stimuli influence approach behaviours through cognitive and affective organism states; this study extends their framework to AI personalization stimuli in service platform contexts.

2.4 Trust Transfer Theory

Trust Transfer Theory, developed by McKnight and Chervany (2002) and formalised in the digital context by Stewart (2003), posits that trust does not have to be built independently with each new entity—it can transfer from a trusted source to a new, related entity. In Stewart's (2003) application, familiarity-based trust in an established institution transfers to a new digital intermediary that is affiliated with or endorsed by the institution. In this study, Trust Transfer operates between three nodes: (1) trust in AI technology generally (accumulated through positive AI experiences across platforms and media); (2) trust in the specific AI personalization system of a focal platform; and (3) trust in the focal platform vendor as a service provider. Consumer confidence, built through positive AI personalisation experiences, activates trust in the platform's AI system, which in turn transfers to vendor trust, which then drives purchase decision commitment.

Kim et al. (2009) provided empirical support for a three-stage trust transfer model in mobile commerce, finding that trust in the mobile technology transferred to trust in the mobile vendor, which predicted purchase intention. This study extends this model by inserting consumer confidence as an upstream antecedent of technology-specific trust—proposing that AI personalisation quality builds consumer confidence, confidence activates technology trust, and technology trust transfers to vendor trust that enables high-quality purchase decisions.

2.5 Consumer Confidence in Purchase Decisions

Consumer confidence in purchase decisions is a metacognitive construct reflecting the consumer's subjective certainty that they have sufficient information, evaluation capability, and situational clarity to make a high-quality choice (Wood & Lynch, 2002). It is distinct from mere purchase intention (which can be held with high or low confidence) and from decision satisfaction (which can only be assessed post-purchase). Laroche et al. (2004) established that brand-specific confidence is a stronger predictor of purchase behaviour than attitude alone, because confident consumers are less susceptible to competitive interference at the moment of choice.

In AI-mediated commerce contexts, personalisation quality influences consumer confidence through two pathways. The informational pathway: accurate personalised recommendations reduce the cognitive effort and uncertainty of information search, enabling consumers to feel more informed and therefore more confident (Jiang & Benbasat, 2007). The relational pathway: personalisation that feels individually attuned creates a sense of being 'understood' by the service provider, activating social trust heuristics that enhance confidence beyond what can be explained by information quality alone (Nass & Moon, 2000; Sheth & Kellstadt, 2021).

2.6 Decision Regret and Repeat Purchase Commitment

Decision regret—the negative emotion experienced when a chosen outcome compares unfavourably with what might have been chosen (Zeelenberg & Pieters, 2007)—is the primary post-purchase threat to consumer retention in service platforms. Regret is particularly salient in experience services (restaurants, travel, healthcare) where quality can only be evaluated after consumption and where the counterfactual alternatives remain imaginatively accessible. AI personalisation can reduce regret by improving the match quality between chosen and preferred service options. However, it can also amplify regret if consumers later discover that AI personalisation suppressed alternatives that would have been superior—a form of 'algorithmic regret' that is increasingly documented in platform commerce contexts (Logg et al., 2019).

Repeat purchase commitment—the volitional, affective commitment to making future purchases on the same platform rather than switching to alternatives—is the behavioural manifestation of service loyalty in digital platform contexts (Bhattacherjee, 2001). It is distinguished from habitual repeat purchase by its motivational character: committed repeaters consciously choose the platform despite awareness of alternatives, whereas habitual repeaters may continue from inertia. AI personalisation that enhances decision quality (reducing regret and increasing post-purchase satisfaction) is hypothesised to build committed rather than merely habitual repeat purchase patterns.

2.7 Research Gaps

Four gaps motivate this study. First, no published study has applied ELM to examine how AI literacy moderates the processing route through which AI personalisation stimuli influence consumer confidence in digital service platforms. Second, Trust Transfer as a mediating mechanism between AI-induced confidence and purchase decision quality has not been empirically tested in multi-platform service contexts. Third, the distinction between decision confidence (subjective) and decision quality (objective-proxied through regret minimisation and satisfaction) as separate dependent variables in AI personalisation research has been conceptualised but not operationalised in SEM frameworks. Fourth, the five AI personalisation dimensions specified in this study—encompassing the full personalisation stack from search ranking through post-purchase follow-up—have not been simultaneously examined in a single framework for Indian digital service platforms.

3. STATEMENT OF THE PROBLEM, OBJECTIVES & HYPOTHESES

3.1 Statement of the Problem

Indian digital service platforms invest billions of rupees annually in AI personalisation infrastructure, yet platform managers lack granular evidence on which personalisation dimensions most effectively build consumer confidence, how that confidence translates into decision quality (as opposed to merely decision speed), and how trust transfer from AI systems to platform vendors shapes the confidence-to-commitment pathway. The practical consequence of this evidence gap is misallocated personalisation investment: platforms invest disproportionately in recommendation engine accuracy (the most visible and benchmarkable dimension) while underinvesting in adaptive notification timing and post-purchase AI follow-up, which this study's theoretical framework suggests may be equally or more potent confidence builders for specific consumer segments. Furthermore, the ELM prediction that AI literacy moderates personalisation processing routes implies that a single personalisation design cannot optimally serve both high-literacy and low-literacy consumers—a design challenge that requires empirical evidence to navigate.

3.2 Research Objectives

To conceptualise and operationalise five AI personalisation dimensions relevant to Indian digital service platforms as stimulus constructs within the S-O-R framework.

To examine the direct effects of AI personalisation dimensions on consumer confidence and perceived personalisation quality as organism constructs.

To test ELM's central/peripheral route prediction by examining AI literacy and purchase involvement as moderators of the personalisation–confidence relationship.

To assess Trust Transfer as a mediator of the consumer confidence–purchase decision quality relationship.

To examine the effects of consumer confidence and perceived personalisation quality on three purchase decision outcomes: decision quality, decision regret minimisation, and repeat purchase commitment.

To conduct platform-level comparative analysis across five digital service platforms in India.

To develop and validate the ELM-S-O-R-Trust Transfer (ESOTT) integrated structural model.

3.3 Research Hypotheses

Group H1: AI Personalisation Stimuli → Consumer Confidence (S-O-R Pathway)

H1a: Predictive Recommendation Fit is positively associated with Consumer Confidence.

H1b: Dynamic Pricing Personalisation is positively associated with Consumer Confidence.

H1c: Personalised Search Ranking is positively associated with Consumer Confidence.

H1d: Adaptive Push Notification Timing is positively associated with Consumer Confidence.

H1e: AI-Driven Post-Purchase Follow-Up is positively associated with Consumer Confidence.

Group H2: AI Personalisation Stimuli → Perceived Personalisation Quality

H2a: Predictive Recommendation Fit is positively associated with Perceived Personalisation Quality.

H2b: Personalised Search Ranking is positively associated with Perceived Personalisation Quality.

H2c: AI-Driven Post-Purchase Follow-Up is positively associated with Perceived Personalisation Quality.

Group H3: ELM Moderation – AI Literacy and Involvement

H3a: AI Literacy positively moderates the relationship between Predictive Recommendation Fit and Consumer Confidence (central route amplification).

H3b: Purchase Involvement positively moderates the relationship between Personalised Search Ranking and Consumer Confidence.

H3c: Low AI Literacy consumers show a stronger peripheral cue effect of Dynamic Pricing Personalisation on Consumer Confidence than high AI literacy consumers.

Group H4: Trust Transfer Mediation

H4a: Trust in AI Technology mediates the relationship between Consumer Confidence and Platform Vendor Trust.

H4b: Platform Vendor Trust mediates the relationship between Trust in AI Technology and Purchase Decision Quality.

H4c: The full Trust Transfer pathway (Confidence → AI Trust → Vendor Trust → Decision Quality) constitutes a significant mediation chain.

Group H5: Organism → Response (Purchase Decision Outcomes)

H5a: Consumer Confidence is positively associated with Purchase Decision Quality.

H5b: Consumer Confidence is positively associated with Decision Regret Minimisation.

H5c: Consumer Confidence is positively associated with Repeat Purchase Commitment.

H5d: Perceived Personalisation Quality is positively associated with Purchase Decision Quality.

H5e: Perceived Personalisation Quality is positively associated with Repeat Purchase Commitment.

Group H6: Platform-Level Moderation

H6a: Platform category (food delivery vs. travel vs. healthcare) moderates the relative strength of AI personalisation dimensions on consumer confidence.

H6b: Platform usage experience (tenure in years) positively moderates the Trust Transfer pathway effect.

4. RESEARCH DESIGN

4.1 Research Philosophy and Design

This study adopts a critical realist ontology and a post-positivist epistemology, acknowledging the objective existence of AI personalisation mechanisms while recognising that their psychological effects are mediated by complex, individually-variable cognitive processes. The methodological approach is quantitative-deductive: theoretically derived hypotheses are tested against primary survey data using multivariate statistical techniques. A cross-sectional survey design is employed with multi-group SEM to enable simultaneous hypothesis testing across platform categories. The ESOTT model is tested as a holistic structural system rather than a series of independent pairwise regressions, capturing the sequential mediation and moderated pathways central to the theoretical framework.

4.2 Target Population and Sampling Strategy

The target population comprised adults aged 18–55 in India who were registered users of at least one of the five focal digital service platforms (Swiggy, Zomato, BookMyShow, MakeMyTrip, Practo) and had completed at least three AI-personalised service transactions on that platform in the three months preceding data collection. The three-transaction criterion ensures substantive AI personalisation experience, providing the experiential grounding necessary for valid construct measurement.

A proportional stratified sampling strategy was applied, targeting consumers across five platform sub-samples: Swiggy (n=101), Zomato (n=98), BookMyShow (n=92), MakeMyTrip (n=89), and Practo (n=88). Platform strata were sized proportionally to estimated active user bases in the four metropolitan cities sampled (Mumbai, Delhi-NCR, Bengaluru, Chennai). Respondents were recruited through platform-specific user communities on Reddit, Facebook, and WhatsApp, supplemented by snowball referrals within professional networks. The final analytical sample of 468 respondents was obtained after quality-screening of 524 initial responses, yielding a retention rate of 89.3%. This sample size exceeds Hair et al.'s (2019) recommendation of 10 observations per free parameter, with the ESOTT model containing 44 free parameters requiring a minimum of 440 observations.

4.3 Measurement Instrument

All constructs were measured using multi-item reflective scales adapted from validated published sources with context-specific language modifications for Indian digital service platforms. Predictive Recommendation Fit (5 items) was adapted from Jiang and Benbasat (2007) and Covington et al. (2016). Dynamic Pricing Personalisation (4 items) was adapted from Grewal et al. (2011). Personalised Search Ranking (4 items) was adapted from Pan et al. (2019). Adaptive Push Notification Timing (4 items) was newly developed drawing on Sahoo et al. (2022). AI-Driven Post-Purchase Follow-Up (3 items) was developed from Kumar et al. (2019). AI Literacy (5 items) was adapted from Longoni et al. (2019). Purchase Involvement (4 items) was adapted from Zaichkowsky (1994). Consumer Confidence (5 items) from Laroche et al. (2004). Perceived Personalisation Quality (4 items) from Tam and Ho (2006). Trust in AI Technology (4 items) from McKnight et al. (2011). Platform Vendor Trust (4 items) from Gefen et al. (2003). Purchase Decision Quality (4 items), Decision Regret Minimisation (3 items), and Repeat Purchase Commitment (4 items) from Bhattacherjee (2001) and Zeelenberg and Pieters (2007). All items used a 5-point Likert scale. A pilot test (n=46) confirmed $\alpha > 0.72$ for all constructs and informed three item revisions.

4.4 Data Collection

Primary data collection was conducted over seven weeks (February–March 2025) via a Qualtrics online survey. Platform-stratified recruitment links were distributed through targeted social media and messaging app channels. Survey quality was controlled through: (a) three attention filter questions embedded at non-sequential positions; (b) minimum response time enforcement (200 seconds); (c) reverse-coded items for acquiescence bias detection; and (d) Mahalanobis distance analysis for multivariate outlier detection ($p < 0.001$ threshold). Respondents received platform-specific digital discount vouchers (₹50–₹100 value) as participation incentives. Ethical approval was obtained from the institutional review board, and informed digital consent was collected from all participants.

4.5 Analytical Approach

Five-stage analysis: (1) Descriptive statistics and frequency profiling; (2) CMV assessment—Harman's Single Factor Test, marker variable technique, ULMC analysis; (3) Measurement model CFA in AMOS 27.0—reliability (Cronbach's α, CR), convergent validity (AVE), discriminant validity (HTMT), and model fit indices; (4) Structural model testing—direct effects (H1, H2, H5), ELM moderation via product-indicator method (H3), sequential Trust Transfer mediation via bootstrap resampling with 5,000 iterations (H4), platform-level multi-group SEM (H6); (5) Explanatory power assessment and effect size reporting (f^2).

5. DEMOGRAPHIC PROFILE OF THE RESPONDENTS

Table 1 presents the demographic profile of the 468 respondents across the five digital service platform sub-samples.

Variable	**Category**	**Swiggy (n=101)**	**Zomato (n=98)**	**BookMyShow (n=92)**	**MakeMyTrip (n=89)**	**Practo (n=88)**	**Total N=468**
Gender	Male	56 (55.4%)	55 (56.1%)	47 (51.1%)	51 (57.3%)	43 (48.9%)	252 (53.8%)
	Female	43 (42.6%)	40 (40.8%)	43 (46.7%)	36 (40.4%)	43 (48.9%)	205 (43.8%)
	Other / NDA	2 (2.0%)	3 (3.1%)	2 (2.2%)	2 (2.2%)	2 (2.3%)	11 (2.4%)
Age	18–24 years	39 (38.6%)	38 (38.8%)	34 (37.0%)	28 (31.5%)	24 (27.3%)	163 (34.8%)
	25–34 years	41 (40.6%)	38 (38.8%)	36 (39.1%)	37 (41.6%)	35 (39.8%)	187 (39.9%)
	35–44 years	15 (14.9%)	16 (16.3%)	16 (17.4%)	18 (20.2%)	21 (23.9%)	86 (18.4%)
	45–55 years	6 (5.9%)	6 (6.1%)	6 (6.5%)	6 (6.7%)	8 (9.1%)	32 (6.8%)
Education	Undergraduate	48 (47.5%)	46 (46.9%)	43 (46.7%)	41 (46.1%)	41 (46.6%)	219 (46.8%)

Variable	Category	Swiggy (n=101)	Zomato (n=98)	BookMyShow (n=92)	MakeMyTrip (n=89)	Practo (n=88)	Total N=468
	Postgraduate	41 (40.6%)	38 (38.8%)	37 (40.2%)	37 (41.6%)	36 (40.9%)	189 (40.4%)
	Doctoral/Prof.	12 (11.9%)	14 (14.3%)	12 (13.0%)	11 (12.4%)	11 (12.5%)	60 (12.8%)
Income	< ₹25,000/mo	23 (22.8%)	22 (22.4%)	19 (20.7%)	16 (18.0%)	17 (19.3%)	97 (20.7%)
	₹25k–₹50k	34 (33.7%)	32 (32.7%)	30 (32.6%)	28 (31.5%)	28 (31.8%)	152 (32.5%)
	₹50k–₹1L	29 (28.7%)	28 (28.6%)	28 (30.4%)	30 (33.7%)	28 (31.8%)	143 (30.6%)
	> ₹1 Lakh	15 (14.9%)	16 (16.3%)	15 (16.3%)	15 (16.9%)	15 (17.0%)	76 (16.2%)
AI Literacy	Low	22 (21.8%)	21 (21.4%)	20 (21.7%)	18 (20.2%)	18 (20.5%)	99 (21.2%)
	Moderate	47 (46.5%)	44 (44.9%)	42 (45.7%)	40 (44.9%)	40 (45.5%)	213 (45.5%)
	High	32 (31.7%)	33 (33.7%)	30 (32.6%)	31 (34.8%)	30 (34.1%)	156 (33.3%)
Platform Tenure	< 1 year	26 (25.7%)	24 (24.5%)	20 (21.7%)	18 (20.2%)	19 (21.6%)	107 (22.9%)
	1–2 years	38 (37.6%)	36 (36.7%)	34 (37.0%)	33 (37.1%)	33 (37.5%)	174 (37.2%)
	3–4 years	27 (26.7%)	26 (26.5%)	24 (26.1%)	24 (27.0%)	23 (26.1%)	124 (26.5%)
	> 4 years	10 (9.9%)	12 (12.2%)	14 (15.2%)	14 (15.7%)	13 (14.8%)	63 (13.5%)
Monthly Transactions	1–3 times	21 (20.8%)	20 (20.4%)	28 (30.4%)	23 (25.8%)	36 (40.9%)	128 (27.4%)
	4–7 times	48 (47.5%)	46 (46.9%)	38 (41.3%)	39 (43.8%)	34 (38.6%)	205 (43.8%)
	> 7 times	32 (31.7%)	32 (32.7%)	26 (28.3%)	27 (30.3%)	18 (20.5%)	135 (28.8%)
City	Metro	76 (75.2%)	72 (73.5%)	67 (72.8%)	64 (71.9%)	62 (70.5%)	341 (72.9%)
	Tier-2	25 (24.8%)	26 (26.5%)	25 (27.2%)	25 (28.1%)	26 (29.5%)	127 (27.1%)

Table 1 presents the demographic profile of the 468 respondents across the five digital service platform sub-samples.

Table 1: Demographic Profile of Respondents (N = 468)

The sample is broadly balanced across platforms and demographic strata. The 18–34 age cohort constitutes 74.7% of respondents, reflecting the digital-native orientation of active service platform users in India. Gender distribution is approximately balanced (53.8% male), with Practo showing near-equal gender split, consistent with healthcare service platform usage patterns. Educational attainment is high (87.2% bachelor's degree or above), commensurate with the urban, smartphone-enabled consumer base characteristic of these platforms. AI literacy distribution across the three levels (Low: 21.2%, Moderate: 45.5%, High: 33.3%) provides adequate variance for ELM moderation analysis. Platform tenure is well distributed, with 76.6% having used their primary platform for over a year, ensuring substantive AI personalisation exposure. Swiggy and Zomato show the highest transaction frequencies (>7 times/month: ~32%), reflecting food delivery's inherently high purchase frequency, while Practo shows the lowest, consistent with healthcare's episodic service pattern.

6. DATA ANALYSIS & MODEL DEVELOPMENT

6.1 Common Method Variance Assessment

Three CMV diagnostics were applied. Harman's Single Factor Test yielded a first unrotated factor accounting for 21.6% of total variance (threshold < 50%). A theoretically unrelated marker variable (need for cognition, 3 items) was included in the survey; partialling it out produced coefficient changes of $\Delta\beta < 0.022$ for all focal paths. An Unmeasured Latent Method Construct (ULMC) added to the CFA produced negligible factor loading improvements ($\Delta\lambda < 0.05$ for all items). Collectively, these diagnostics confirm that CMV does not materially distort the study's findings.

6.2 Measurement Model: CFA Results and Validity

CFA in AMOS 27.0 using Maximum Likelihood Estimation yielded excellent overall fit: $\chi^2(893) = 1{,}587.2$, $\chi^2/df = 1.78$, CFI = 0.967, TLI = 0.963, RMSEA = 0.040 (90% CI: 0.036–0.044), SRMR = 0.045. Table 2 presents the full measurement model statistics.

Table 2: CFA Measurement Model – Reliability and Validity (N = 468)

All Cronbach's alpha values exceed 0.86 and CR values exceed 0.87, substantially above the 0.70 reliability threshold. AVE values range from 0.671 to 0.802, all exceeding the 0.50 convergent validity benchmark. Discriminant validity is confirmed by HTMT ratios below 0.85 for all construct pairs (maximum = 0.738). Standardised factor loadings range from 0.71 to 0.94 (all $p < 0.001$) with no significant cross-loadings, confirming items' construct specificity. These results validate the measurement model as psychometrically sound for structural testing.

Construct (Items)	**α**	**CR**	**AVE**	**MSV**	**HTMT Max**	**Load Range**
Pred. Recommendation Fit – PRF (5)	0.928	0.932	0.732	0.348	0.627	0.78–0.94
Dynamic Pricing Personalisation – DPP (4)	0.897	0.904	0.703	0.308	0.581	0.74–0.91
Personalised Search Ranking – PSR (4)	0.891	0.898	0.688	0.289	0.563	0.73–0.90
Adaptive Push Notif. Timing – APNT (4)	0.883	0.891	0.671	0.276	0.548	0.71–0.89
AI Post-Purchase Follow-Up – APPF (3)	0.864	0.876	0.702	0.261	0.524	0.77–0.88
AI Literacy – AIL (5)	0.917	0.922	0.704	0.287	0.531	0.74–0.91
Purchase Involvement – PI (4)	0.888	0.895	0.681	0.271	0.512	0.72–0.90
Consumer Confidence – CC (5)	0.938	0.941	0.761	0.412	0.723	0.79–0.94
Perceived Personal. Quality – PPQ (4)	0.909	0.915	0.729	0.387	0.698	0.78–0.93
Trust in AI Technology – TAT (4)	0.921	0.926	0.756	0.401	0.716	0.79–0.93
Platform Vendor Trust – PVT (4)	0.913	0.918	0.737	0.389	0.704	0.78–0.92
Purchase Decision Quality – PDQ (4)	0.934	0.938	0.791	0.442	0.738	0.81–0.94
Decision Regret Minimisation – DRM (3)	0.919	0.924	0.802	0.418	0.711	0.83–0.93
Repeat Purchase Commitment – RPC (4)	0.926	0.930	0.769	0.427	0.724	0.80–0.93

6.3 Structural Model: Direct Effects (H1, H2, H5)

The full ESOTT structural model was estimated using Maximum Likelihood Estimation. Overall model fit is excellent: $\chi^2/df = 1.92$, CFI = 0.963, TLI = 0.958, RMSEA = 0.044 (90% CI: 0.040–0.049), SRMR = 0.050. Table 3 presents all direct path estimates.

Table 3: Structural Model – Direct Path Coefficients (N = 468)

Hyp.	Structural Path	β (Std.)	S.E.	t-value	p-value	R^2	Result
H1a	PRF → Consumer Confidence	0.462	0.045	10.267	***	—	Supported
H1b	DPP → Consumer Confidence	0.287	0.052	5.519	***	—	Supported
H1c	PSR → Consumer Confidence	0.254	0.054	4.704	***	—	Supported
H1d	APNT → Consumer Confidence	0.318	0.050	6.360	***	0.718	Supported
H1e	APPF → Consumer Confidence	0.231	0.055	4.200	***	—	Supported
H2a	PRF → Perceived Person. Quality	0.441	0.046	9.587	***	—	Supported
H2b	PSR → Perceived Person. Quality	0.378	0.049	7.714	***	0.694	Supported
H2c	APPF → Perceived Person. Quality	0.312	0.053	5.887	***	—	Supported
H5a	CC → Purchase Decision Quality	0.487	0.044	11.068	***	—	Supported
H5b	CC → Decision Regret Minimisation	0.463	0.046	10.065	***	—	Supported
H5c	CC → Repeat Purchase Commitment	0.412	0.049	8.408	***	—	Supported
H5d	PPQ → Purchase Decision Quality	0.341	0.051	6.686	***	0.718	Supported
H5e	PPQ → Repeat Purchase Commitment	0.298	0.053	5.623	***	0.684	Supported

6.4 ELM Moderation Analysis (H3)

Note: *** $p < 0.001$; β = standardised path coefficient; S.E. = standard error. PRF = Predictive Recommendation Fit; DPP = Dynamic Pricing Personalisation; PSR = Personalised Search Ranking; APNT = Adaptive Push Notification Timing; APPF = AI Post-Purchase Follow-Up; CC = Consumer Confidence; PPQ = Perceived Personalisation Quality. R^2 values are reported for endogenous constructs (Consumer Confidence: 0.718; Perceived Personalisation Quality: 0.694; Purchase Decision Quality: 0.718; DRM: 0.684; RPC: full model $R^2 = 0.673$).

All thirteen direct-effect hypotheses are supported. PRF is the dominant predictor of Consumer Confidence (β = 0.462), confirming the primacy of predictive accuracy in confidence formation. APNT (β = 0.318) emerges as the second-ranked predictor, suggesting that the timeliness of AI interventions—not merely their accuracy—is a significant, and potentially undervalued, confidence driver. Consumer Confidence most strongly predicts Purchase Decision Quality (β = 0.487), establishing the organism-to-response conversion as robust in digital service platform contexts.

6.5 Trust Transfer Mediation Analysis (H4)

H3a is supported: AI Literacy significantly positively moderates the PRF → Consumer Confidence relationship ($\beta\_mod = 0.224$, $t = 5.48$, $p < 0.001$, $\Delta R^2 = 0.038$). Simple slopes analysis confirms the ELM prediction: at high AI literacy (+1 SD), PRF → CC is substantially stronger (β = 0.621) than at low AI literacy (–1 SD, β = 0.298), consistent with high-literacy consumers processing recommendation accuracy through the central route with higher elaboration and stronger attitude change. H3b is supported: Purchase Involvement positively moderates PSR → CC ($\beta\_mod = 0.187$, $t = 4.51$, $p < 0.001$). H3c is partially supported: low AI literacy consumers show a marginally stronger DPP → CC relationship (β = 0.341) than high literacy consumers (β = 0.239), consistent with peripheral cue processing, though the interaction term reaches only conventional significance ($\beta\_mod = –0.102$, $t = –2.47$, $p = 0.014$).

Hyp.	Mediation Chain	Direct β	Indirect β	95% BCa CI	Prop. Mediated	Type
H4a	CC → TAT → PVT	0.234***	0.287***	[0.231, 0.348]	55.1%	Partial
H4b	TAT → PVT → PDQ	0.198***	0.241***	[0.189, 0.298]	54.9%	Partial
H4c	CC → TAT → PVT → PDQ	0.187***	0.198***	[0.153, 0.248]	51.4%	Partial

6.6 Platform-Level Comparative Analysis (H6)

Sequential mediation was tested via bootstrapping (5,000 resamples). Table 4 presents mediation results.

6.7 Explained Variance and Effect Sizes

Table 4: Trust Transfer Sequential Mediation Results (N = 468, Bootstrap = 5,000)

Note: *** $p < 0.001$; CC = Consumer Confidence; TAT = Trust in AI Technology; PVT = Platform Vendor Trust; PDQ = Purchase Decision Quality; BCa = Bias-Corrected and Accelerated bootstrap CI.

All three Trust Transfer mediation hypotheses are supported. The full chain (H4c: CC → TAT → PVT → PDQ) is significant with indirect β = 0.198, demonstrating that trust transfer operates as a complete psychological pathway converting AI-induced confidence into purchase decision quality through sequential trust migration from technology to vendor. The partial mediation in all pathways indicates that consumer confidence also exerts direct purchase quality effects independent of trust transfer, confirming that confidence and trust are complementary but not redundant mechanisms.

6.6 Platform-Level Comparative Analysis (H6)

Multi-group SEM analysis examined platform-level structural invariance. H6a is supported: significant cross-platform variation is observed for APNT → CC (χ^2diff = 12.41, $p < 0.01$)—Swiggy and Zomato (food delivery) show markedly stronger APNT effects (β = 0.412 and 0.398) than Practo (healthcare, β = 0.187), reflecting food delivery's habit-driven, timing-sensitive usage pattern. PRF → CC is strongest for MakeMyTrip (β = 0.521) and BookMyShow (β = 0.498), consistent with high-involvement, infrequent travel and entertainment decisions where accuracy carries greater confidence stakes. Practo shows the strongest APPF → PPQ path (β = 0.441), reflecting healthcare's unique reliance on post-consultation AI follow-up for care plan adherence and appointment management. H6b is supported: platform tenure positively moderates the Trust Transfer pathway (β_mod = 0.167, t = 3.89, $p < 0.001$), confirming that accumulated platform experience deepens the efficiency of trust transfer from AI systems to vendors.

6.7 Explained Variance and Effect Sizes

The ESOTT model explains 71.8% of variance in Purchase Decision Quality, 68.4% in Repeat Purchase Commitment, and 67.2% in Decision Regret Minimisation. Effect sizes (Cohen's f^2) are large for the PRF → CC path ($f^2 = 0.521$) and the CC → PDQ path ($f^2 = 0.478$), and medium for the Trust Transfer mediation pathway ($f^2 = 0.234$), confirming both statistical and practical significance of the model's key mechanisms.

7. FINDINGS

Finding 1: Predictive Recommendation Fit Anchors the Confidence Formation Architecture

Predictive Recommendation Fit emerges as the dominant driver of Consumer Confidence (β = 0.462)—substantially outpacing Dynamic Pricing (β = 0.287), Personalised Search Ranking (β = 0.254), and even AI Post-Purchase Follow-Up (β = 0.231). This finding establishes recommendation accuracy as the foundational confidence mechanism: when AI systems surface options that consumers experience as genuinely fitting their unarticulated preferences, the resulting cognitive consonance generates a powerful confidence signal. The implication extends the informational adequacy framework of Jiang and Benbasat (2007) by confirming that it is not merely the quantity of information provided but the perceived precision of AI preference modelling that constitutes the primary confidence driver in service platform AI.

Finding 2: Adaptive Notification Timing is a Disproportionately Valuable Confidence Lever

The finding that Adaptive Push Notification Timing (APNT) is the second-ranked confidence predictor (β = 0.318) and shows the largest cross-platform variation in effect size challenges current industry investment allocation patterns, which prioritise recommendation engine accuracy. The APNT finding suggests that consumers interpret timely AI interventions—notifications that arrive at decision-relevant moments—as evidence of AI attentiveness and understanding, generating confidence that is qualitatively similar to the confidence produced by accurate content recommendations. In high-frequency, habit-driven platform categories (food delivery), timing precision may even substitute for recommendation accuracy as the primary confidence cue, particularly for consumers who already trust the platform's content curating ability.

Finding 3: ELM Route Differentiation is Empirically Validated in AI Commerce

The moderation findings (H3a: β_mod = 0.224; H3b: β_mod = 0.187) provide the first large-sample empirical validation of ELM's central/peripheral route prediction in an AI personalization context. High-literacy consumers form confidence through careful central route evaluation of recommendation accuracy and search ranking quality (elevated PRF → CC: β = 0.621 at high literacy). Low-literacy consumers rely on peripheral cues—pricing presentation, notification frequency, interface aesthetic polish—as heuristic confidence signals (elevated DPP → CC at low literacy). This route differentiation has direct design implications: a single AI personalization interface cannot simultaneously optimise central and peripheral route confidence formation, requiring adaptive interface design that detects and responds to individual AI literacy levels.

Finding 4: Trust Transfer is the Pivotal Confidence-to-Purchase Quality Bridge

The sequential Trust Transfer mediation chain (CC → TAT → PVT → PDQ: indirect β = 0.198, 95% CI [0.153, 0.248]) reveals a novel mechanism absent from prior AI commerce trust literature: consumer confidence, built through AI personalisation quality, activates trust in the AI technology system, which then transfers to trust in the platform vendor, which ultimately elevates the quality of purchase decisions made. This three-node trust transfer model extends Stewart's (2003) two-node framework by inserting AI technology trust as an intermediary node between confidence and vendor trust—a theoretically important extension given that AI systems increasingly constitute a distinct identifiable agent in the consumer's perceptual field, not merely a transparent platform capability.

Finding 5: Post-Purchase AI Follow-Up Drives Perceived Personalisation Quality, Not Confidence

AI-Driven Post-Purchase Follow-Up (APPF) shows a significant and substantial path to Perceived Personalisation Quality (β = 0.312) but a comparatively smaller path to Consumer Confidence (β = 0.231). This asymmetry reveals that post-purchase AI interactions—personalised review prompts, reorder suggestions, care plan reminders—primarily contribute to the consumer's holistic evaluation of personalisation quality rather than to immediate decision confidence. The finding establishes APPF as primarily a loyalty and quality perception mechanism rather than a confidence mechanism, suggesting that platforms should design post-purchase AI personalisation specifically to reinforce the quality narrative of completed transactions rather than to drive future purchase confidence.

Finding 6: Platform Category Determines the Most Potent Personalisation Lever

The cross-platform variation findings establish that AI personalisation's most effective confidence drivers are category-contingent. In food delivery (Swiggy, Zomato), timing precision (APNT) is the primary confidence driver, reflecting the high purchase frequency and time-sensitivity of this category. In travel and entertainment (MakeMyTrip, BookMyShow), recommendation accuracy (PRF) dominates, reflecting high purchase involvement and the relative infrequency of transactions. In healthcare (Practo), post-purchase follow-up quality (APPF → PPQ) is uniquely prominent, reflecting healthcare's extended service consumption cycle and the importance of ongoing AI-supported care management in this category. These category-specific patterns argue strongly against platform-agnostic AI personalisation design frameworks.

Finding 7: Consumer Confidence Predicts Decision Quality Beyond Mere Purchase Intention

The finding that Consumer Confidence significantly predicts not only Purchase Decision Quality (β = 0.487) but also Decision Regret Minimisation (β = 0.463) provides empirical support for the study's conceptual distinction between confidence-driven decision quality and mere purchase intention. Confident consumers make better decisions—choices they are less likely to regret post-purchase—not merely more frequent decisions. This distinction has significant implications for how e-commerce platforms measure AI personalisation ROI: platforms that measure only purchase rate without measuring post-purchase satisfaction and regret are capturing only part of personalisation's value, and potentially missing interventions that elevate decision quality at the expense of decision speed.

Finding 8: Dynamic Pricing Personalisation Has Both Confidence and Peripheral Cue Effects

Dynamic Pricing Personalisation shows a direct positive confidence effect (β = 0.287) and also exhibits the strongest peripheral cue effect at low AI literacy (H3c: low-literacy β = 0.341 vs. high-literacy β = 0.239). This dual character—genuine confidence builder for all consumers and peripheral heuristic cue for low-literacy consumers—establishes personalised pricing as a versatile confidence mechanism that serves both ELM processing routes. However, it also raises an ethical design challenge: platforms that optimise personalised pricing as a peripheral confidence signal may exploit low-literacy consumers' limited ability to evaluate pricing fairness through central route processing.

8. MANAGERIAL IMPLICATIONS

8.1 Invest in the Full AI Personalisation Stack, Not Just Recommendation Engines

The finding that five distinct personalisation dimensions each independently contribute to consumer confidence argues against the common platform strategy of concentrating AI investment in recommendation engine accuracy while underinvesting in adaptive notification timing, personalised search ranking, and post-purchase AI follow-up. Platform AI product managers should conduct personalisation stack audits measuring the current capability maturity and consumer confidence impact of each dimension separately, then allocate incremental investment to the dimensions with the highest marginal confidence ROI given current maturity levels. For most platforms, this analysis will reveal that APNT and APPF—which are typically less mature than recommendation engines—offer the highest marginal returns on additional investment.

8.2 Design AI Literacy-Adaptive Interfaces Based on ELM Principles

The ELM moderation finding that high-literacy consumers process AI personalisation cues centrally while low-literacy consumers rely on peripheral heuristics requires platform UX managers to develop AI literacy-adaptive interface designs. For high-literacy users (identifiable through engagement with personalisation settings, explicit preference management, and technical feature usage patterns): provide detailed, data-supported recommendation explanations; enable preference profile visibility and editing; and surface accuracy statistics (e.g., '87% of users with your profile liked this restaurant'). For low-literacy users: prioritise visual confidence cues (high star ratings, strong social proof badges, prominent 'Recommended for you' labelling); simplify pricing presentation with clear savings calculators; and use emotionally resonant imagery in notifications. Platforms should A/B test literacy-stratified designs measuring consumer confidence surveys and purchase quality outcomes, not merely click rates.

8.3 Operationalise the Trust Transfer Pathway as a Retention Strategy

The Trust Transfer finding (CC → TAT → PVT → PDQ) provides a three-stage consumer retention model that platform managers can operationalise. Stage 1 (AI Trust Building): invest in AI reliability communications—proactive acknowledgement of recommendation errors, public model performance metrics, 'How our AI works' consumer education content—to build technology-specific trust grounded in accurate AI performance expectations. Stage 2 (Trust Transfer Facilitation): establish clear symbolic and communicative links between the platform's AI system and the brand identity—positioning the AI as a valued team member ('Your Swiggy food guide') rather than an anonymous algorithm— to facilitate trust migration from technology to vendor. Stage 3 (Decision Quality Reinforcement): implement post-purchase AI satisfaction measurement that explicitly links decision quality to AI personalisation quality, creating a feedback loop that reinforces the Trust Transfer mechanism through confirmed expectation cycles.

9. SCOPE FOR FURTHER RESEARCH

9.1 ELM Route Tracking Through Process Tracing

The ELM moderation findings are based on product-indicator interaction terms, which provide statistical evidence of route moderation but cannot directly observe the processing route. Future research should employ process-tracing methodologies—cognitive load measurement, think-aloud protocols, eye-tracking, and mouse-movement trajectory analysis—to directly observe central vs. peripheral processing of AI personalisation cues in real-time digital platform interactions. This would provide mechanistic validation of the ELM-based confidence formation pathways proposed in this study.

9.2 Trust Transfer in Multi-Platform Ecosystems

This study examined Trust Transfer within a single platform context. However, Indian consumers increasingly navigate multi-platform digital ecosystems where AI trust established on one platform may transfer to a related platform within the same corporate ecosystem (e.g., Swiggy and Zomato as competing platforms within the food delivery category, or Amazon and Alexa as complementary platforms within the same ecosystem). Future research should examine cross-platform and cross-ecosystem trust transfer dynamics, investigating whether positive AI trust on a primary platform accelerates AI trust formation on secondary platforms within and across corporate ecosystems.

9.3 Generative AI and Conversational Personalisation

The rapid deployment of large language model (LLM)-powered conversational AI features—including Zomato's AI food guide, Swiggy's chat ordering assistant, and healthcare chatbot consultations—introduces qualitatively new AI personalisation dimensions not captured by this study's five-stimulus framework. Future research should develop and validate conversational AI-specific personalisation constructs (dialogue naturalness, empathetic response quality, memory continuity across interactions) and examine how they interact with the existing ELM processing routes and Trust Transfer mechanism identified in this study.

9.4 Longitudinal Trust Accumulation and Decay

The cross-sectional design precludes examination of how AI-induced trust accumulates through repeated positive interactions and decays following AI failures. Future longitudinal panel research should track individual consumers across at least 12 months of platform usage, capturing AI personalisation quality evaluations, consumer confidence levels, trust ratings, and purchase decision outcomes at monthly intervals. This would enable modelling of trust trajectory dynamics, including the rate of trust accumulation per positive AI interaction, the magnitude of trust decay per AI failure, and the asymmetry between accumulation and decay rates.

9.5 AI Personalisation in Healthcare: Ethics and Confidence

Practo's distinct AI personalisation effect profile—particularly the primacy of post-purchase (post-consultation) AI follow-up—highlights healthcare as a domain that requires specialised AI personalisation research frameworks. Future research should examine the unique ethical dimensions of AI-driven medical recommendation personalisation: how patient autonomy interacts with algorithmic deference; the role of clinical authority trust in the AI trust formation process; the regulatory requirements of India's Telemedicine Practice Guidelines for AI-assisted healthcare recommendations; and the consequences of AI recommendation-induced confidence in medical decision-making where overconfidence can be dangerous.

9.6 Cross-Cultural Replication

This study's findings are specific to the Indian digital service platform context. Future cross-national replication studies should examine whether the ELM route differentiation finding generalises across cultural contexts with different AI familiarity distributions, privacy norms, and digital infrastructure maturity levels. Particularly, comparison between India's high-growth, digitally-heterogeneous market and mature high-AI-literacy markets (South Korea, Japan, United States) would test whether ELM moderation effects diminish as AI literacy converges across populations—a theoretically important test of the framework's long-term applicability.

9.7 AI Personalisation and Consumer Wellbeing

While this study focuses on decision quality and platform retention outcomes, a critical under-researched dimension of AI personalisation effects is consumer wellbeing. AI personalisation that maximises confidence and purchase frequency may simultaneously compromise consumer financial wellbeing (through impulse purchase facilitation), dietary wellbeing (through food delivery over-ordering), or information wellbeing (through filter bubble formation in content-adjacent platforms). Future research should develop and apply consumer wellbeing impact frameworks to AI personalisation systems, examining the trade-offs between platform economic objectives and individual consumer welfare outcomes.

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