The Algorithmic Impulse: AI-Driven Personalisation, Perceived Relevance, and Impulse Buying in Contemporary Indian E-Commerce - A Mediated Path Analysis with Age Moderation

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ABSTRACT

The rapid diffusion of artificial intelligence into the retail value chain compels contemporary businesses to move beyond operational efficiency arguments toward a richer understanding of how algorithmic interventions reshape consumer psychology. This study investigates the mechanism through which AI-based personalisation precipitates impulse buying behaviour on Indian e-commerce platforms, positing Perceived Relevance as the critical psychological mediator and Age as a boundary-condition moderator. Grounded in the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974) and informed by its contemporary extension toward the Stimulus-Organism-Behaviour-Consequence (SOBC) paradigm, the study deployed a structured Likert-scale survey instrument administered to 247 active online shoppers in India.

Path analysis using a three-step ordinary least squares (OLS) mediation approach (Baron & Kenny, 1986) produced clear results. AI personalization significantly predicts Perceived Relevance ($\beta = 0.772$, $R^2 = 0.616$, $p < .001$), and Perceived Relevance, in turn, significantly predicts impulse purchasing ($\beta = 0.596$, $R^2 = 0.358$, $p < .001$). Importantly, the Sobel test supports complete mediation: the direct impact of AI personalization on impulse buying, which is initially significant ($\beta = 0.477$, $p < .001$), becomes statistically non-significant ($\beta = 0.045$, $p = .576$) after adding the mediator, whereas the indirect effect remains strongly significant (0.432; $z = 6.421$, $p < .001$). Additional analysis shows that shopping frequency significantly moderates impulse propensity ($F = 5.118$, $p = .002$), while gender does not ($p = .579$). Age-based comparisons also suggest that the 18–25 (Gen Z) group displays the greatest personalization–relevance sensitivity; however, limited group sizes prevent drawing formal conclusions about moderation. Reliability for all constructs were within the range (α range: 0.883–0.927).

These findings carry direct strategic weight for contemporary businesses: the ROI of recommendation engines is not a function of algorithmic sophistication alone, but of the consumer's subjective experience of relevance. For Indian e-commerce platforms operating in a high-competition, mobile-first environment, the imperative is to invest in contextual, transparent, and culturally attuned personalisation. The study also foregrounds urgent ethical tensions surrounding algorithmic nudging, consumer autonomy, and the Digital Personal Data Protection Act (DPDPA), 2023.

Keywords: *AI-based personalisation, impulse buying behaviour, perceived relevance, S-O-R framework, e-commerce, consumer behaviour, Gen Z*

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1. INTRODUCTION

Every significant e-commerce transaction today is preceded by an invisible exchange between a consumer's latent preferences and an artificial intelligence system's prediction of what those preferences are. On platforms such as Amazon, Flipkart, and Myntra, machine learning models trained on billions of behavioural data points construct real-time recommendation carousels that arrive in the consumer's perceptual field before the consumer has consciously formulated a purchase intention. In this sense, the algorithm anticipates the consumer. The strategic and psychological consequences of this anticipation are the central concern of this research.

The implications for contemporary business are substantial. McKinsey & Company (2023) estimated that organizations that implement personalization at scale report revenue gains ranging from 10–15%. Shamim and Misra (2025) report that the pathway from AI personalisation to revenue is mediated by hedonic value activation — the consumer must enjoy the experience of being understood. Yet the foundational issue of mechanism remains unresolved with the degree of precision sought by businesses: specifically, which psychological conditions cause an AI recommendation to precipitate an impulsive, unplanned purchase. This issue extends beyond the purely academic domain. It determines the design of recommendation engines, the calibration of push notification timing, the blueprint of checkout flows, and the governance frameworks that regulators are presently developing for these same systems.

This study presents a theoretically grounded and empirically validated claim: the link from AI personalization to impulse buying is neither direct nor automatic. Instead, it passes through an essential cognitive and affective checkpoint — Perceived Relevance, defined as the consumer's subjective judgment that a recommendation meaningfully aligns with their immediate needs, preferences, or aspirations. A technically sophisticated personalisation engine that generates recommendations perceived as irrelevant will not induce impulse purchasing. Conversely, one that generates recommendations experienced as uncannily accurate converts the browsing consumer into the buying consumer. The entire commercial ROI of personalisation, this study argues, is locked behind this relevance gateway.

The study is situated within the Indian digital retail context, which is particularly illuminating for the conference theme of AI's implications for contemporary business. India presents a unique confluence of factors: over 200 million active e-commerce users (IBEF, 2023), a predominantly young and digitally native consumer population, rapidly expanding AI-powered retail infrastructure, and the recent enactment of the Digital Personal Data Protection Act (DPDPA), 2023 — which places legal constraints on the very personalisation mechanisms this study analyses. In this context, comprehending the psychological foundations of AI-driven consumer behavior is simultaneously relevant to business strategy, adherence to regulatory requirements, and consumer well-being.

The paper proceeds as follows. Section 2 develops the theoretical framework and reviews contemporary literature on AI personalisation, perceived relevance, and impulse buying within the S-O-R and SOBC paradigms. Section 3 presents the research model and formal hypotheses. Section 4 describes the methodology. Section 5 reports the data analysis in full, including reliability testing, correlation analysis, path analysis, mediation testing, and supplementary group comparisons. Section 6 interprets the findings in the context of contemporary business strategy, ethical AI governance, and the specific contours of the Indian market. Section 7 concludes.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

This review is organised around the four constructs central to the proposed model. Section 2.1 situates the study within the S-O-R and SOBC theoretical traditions; Section 2.2 reviews the mechanisms through which AI personalisation influences buying behaviour; Section 2.3 examines Perceived Relevance as the psychological process mediating this influence; and Section 2.4 reviews the antecedents of impulse buying, before Section 3 translates these strands into the study's formal hypotheses.

2.1 From S-O-R to SOBC: The Evolution of Consumer Behaviour Theory in the AI Era

The Stimulus-Organism-Response (S-O-R) framework, developed by Mehrabian and Russell (1974), provided the foundational architecture for understanding how environmental stimuli condition behavioural outcomes through internal psychological states. In the original formulation, physical retail environments — lighting, layout, scent — constituted the stimuli; approach or avoidance behaviours were the outcomes; and affective states such as pleasure and arousal mediated the relationship. Verhagen and Van Dolen (2011) extended this to the online environment, demonstrating that website beliefs and store quality function analogously to physical environment stimuli in predicting impulse purchases.

Contemporary scholarship, however, has emphasized the need for a more dynamic, consequence-sensitive framework, given that AI systems replace static environmental features with adaptive, responsive, and predictive stimuli. Shamim and Misra (2025) advocate the Stimulus-Organism-Behaviour-Consequence (SOBC) extension, wherein the behavioural outcome is contextualised within a broader consequence landscape that includes post-purchase regret, privacy concern activation, and long-term brand loyalty shifts. Within the SOBC paradigm, AI service quality — characterised by accuracy, timeliness, security, and interface design — functions as the stimulus, while hedonic and utilitarian value perceptions constitute the organism stage. Critically, hedonic value (pleasure, excitement, experiential gratification) has been identified as a significantly stronger predictor of the impulse purchase urge than utilitarian value (efficiency, task completion) (Shamim & Misra, 2025).

The current study is conducted primarily within the S-O-R framework, while also recognizing the SOBC extension. This framework characterizes AI-based personalization as the stimulus, perceived relevance as the organism, and impulse buying behavior as the response. Age is theorized as a moderating boundary condition that determines how sensitively consumers process AI stimuli.

2.2 AI-Based Personalization in Contemporary Business: Strategic Significance and Mechanisms

AI-based personalisation in e-commerce refers to the deployment of machine learning, collaborative filtering, and predictive analytics to deliver tailored product recommendations, dynamic pricing, and contextually relevant content to individual consumers in real time. Xu et al. (2011) established that personalisation positively influences user engagement and satisfaction. More recent scholarship identifies several distinct mechanisms through which AI personalisation influences buying behaviour in contemporary retail contexts.

Haryanto et al. (2025) demonstrate that predictive algorithms function not merely as recommendation tools but as stimulus orchestrators — sequencing product exposures in ways designed to exploit cognitive biases including anchoring, scarcity perception, and recency effects. Lu et al. (2025) further document that AI personalisation in social commerce contexts creates a "recommendation-engagement loop" wherein relevance perceptions drive engagement, which in turn generates more behavioural data, enabling higher recommendation accuracy. This feedback dynamic renders AI personalisation systems self-reinforcing and creates competitive advantages for early adopters of more sophisticated algorithmic infrastructure.

Ahmed et al. (2025) specifically assesses how machine learning algorithms influence personalized digital marketing campaigns, and they report that contextual relevance and delivery timing are the two strongest factors driving purchase intention. Critically, they report that algorithmic accuracy on its own is insufficient — consumers must consciously or semiconsciously register that the recommendation "speaks to" their current situation for any behavioral change to occur.

Rasool et al. (2025) extend this insight to the unplanned purchase domain, showing that ad personalisation triggers customer engagement, which mediates the path to impulse buying. Their moderated mediation model treats prior purchase history as a boundary condition that strengthens the link between personalization and engagement, indicating that habitual platform users are more vulnerable than others to algorithmically triggered impulse purchases.

2.3 Perceived Relevance: The Psychological Process Underlying AI Influence

Perceived Relevance refers to the consumer's subjective judgment that a recommended product or service is meaningfully aligned with their current needs, preferences, or

identity-related aspirations (Tam & Ho, 2006). It functions as a dual cognitive–affective assessment: cognitively, it indicates the consumer's inference that the algorithm reflects their preferences; affectively, it elicits a feeling of confirmation or recognition that strengthens attentional engagement and reduces deliberative resistance to purchase.

Tam and Ho (2006) were among the first to establish empirically that personalisation effects on consumer decision outcomes operate through the relevance appraisal rather than through any technical property of the personalisation system itself. This finding has proven remarkably robust across subsequent decades of research. Nimisha et al. (2025) extend it to the contemporary AI personalisation context, demonstrating that relevance appraisals interact with emotional engagement — when AI recommendations are perceived as relevant and emotionally resonant, the resulting impulse purchase urge is substantially amplified relative to relevance alone.

The relevance gateway has a second, strategically critical, implication: it creates the conditions for what Xu et al. (2011) termed the "personalisation-privacy paradox." Consumers seek the experiential advantages of accurate, relevant recommendations, yet at the same time they resent the data collection and inferential processes that enable these recommendations. Wahdaniyah et al. (2025) document a closely related phenomenon through the Fear of Missing Out (FOMO) lens: AI personalisation activates relevance perceptions, which in turn generates FOMO-driven urgency, which strongly predicts impulse purchases. The mechanism is thus: personalisation → relevance → FOMO → impulse purchase — a chain in which each link amplifies the next.

2.4 Impulse Buying Behaviour: Definition, Antecedents, and Online Dynamics

Dennis Rook (1987) defined impulse buying as the sudden, powerful, and persistent urge to buy something immediately, accompanied by internal conflict and disregard for consequences. Rook and Fisher (1995) subsequently established that impulse buying is not purely an emotional phenomenon but is governed by normative evaluative mechanisms — the consumer assesses whether the impulse is socially and personally appropriate before acting on it. This normative dimension has important implications for AI-driven e-commerce design: platforms that reduce the normative friction associated with impulse purchases (e.g., through social proof, peer purchase visibility, and one-click ordering) amplify the translation of purchase urges into actual transactions.

Sun et al. (2023) demonstrate that AI-based features - personalised recommendations, anticipatory search suggestions, automated wish lists - increase both shopping enjoyment and convenience, both of which independently predict impulse purchase frequency. Wells et al. (2011) identify website quality as a moderating condition, with higher-quality interfaces amplifying the impulse-triggering effect of recommendations. In the contemporary Indian context, mobile-first interface design

and the dominance of super-apps that integrate social, entertainment, and shopping functions create environmental conditions that are particularly conducive to impulse purchasing.

Research Gap and Research Questions

Despite this growing body of literature, a specific gap persists: existing studies have documented that AI personalisation influences engagement, satisfaction, and even impulse purchasing, but few have empirically isolated the psychological mechanism — Perceived Relevance — through which this effect operates, and fewer still have tested whether this mechanism is contingent on the age of the consumer, especially within a mobile-first, digitally native Indian e-commerce context. This study addresses this gap through the following research questions: (i) Does AI-based personalisation significantly influence consumers' Perceived Relevance? (ii) Does Perceived Relevance significantly influence Impulse Buying Behaviour? (iii) Does Perceived Relevance mediate the relationship between AI-based personalisation and Impulse Buying Behaviour? (iv) Does age moderate the relationship between AI-based personalisation and Perceived Relevance? These research questions directly inform the hypotheses developed in Section 3.

3. CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

3.1 Research Model

The proposed research model is grounded in the S-O-R framework and operationalises three constructs: AI-Based Personalisation (Independent Variable / Stimulus), Perceived Relevance (Mediator / Organism), and Impulse Buying Behaviour (Dependent Variable / Response). Age operates as a moderating boundary condition on the Stimulus-Organism path. The model is visualised as follows:

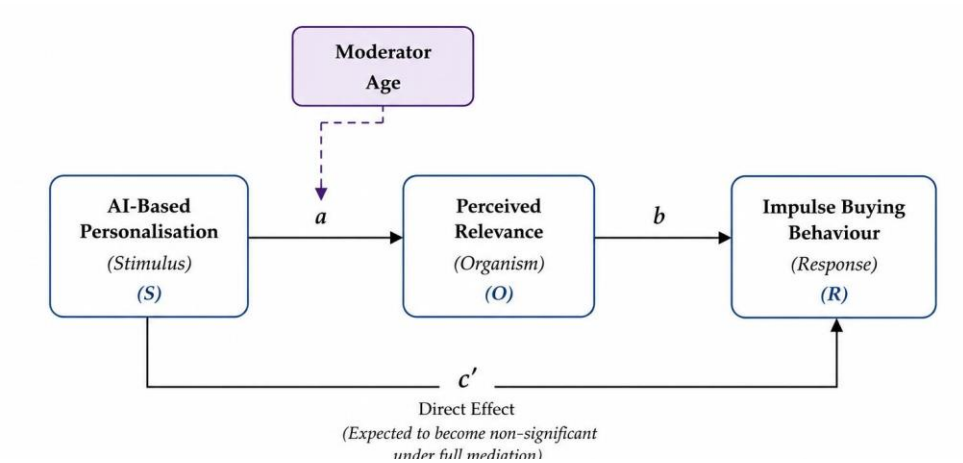


Figure 1. Proposed Research Model Based on the Stimulus–Organism–Response (S–O–R) Framework (Mehrabian & Russell, 1974)

Note. AI-Based Personalisation represents the Stimulus (S), Perceived Relevance represents the Organism (O), and Impulse Buying Behaviour represents the Response (R). Path a = AI Personalisation → Perceived Relevance; Path b = Perceived Relevance → Impulse Buying; Path c′ = direct path after mediation. Age moderates Path a.

3.2 Hypothesis Development

H1: AI-based personalisation positively and significantly influences Perceived Relevance.

Rationale: The foundational argument of Tam and Ho (2006), corroborated by Nimisha et al. (2025) and Lu et al. (2025), holds that personalisation increases the consumer's sense that recommendations are contextually tailored, which constitutes the essence of relevance perception.

H2: Perceived Relevance positively and significantly influences Impulse Buying Behaviour.

Rationale: When recommendations feel personally appropriate, attentional focus narrows, deliberative resistance diminishes, and the hedonic arousal required to convert browsing into buying intensifies (Shamim & Misra, 2025; Rook & Fisher, 1995).

H3: AI-based personalisation positively influences Impulse Buying Behaviour.

Rationale: Prior to mediation testing, a direct association between the stimulus and response is theoretically expected and empirically documented (Haryanto et al., 2025; Rasool et al., 2025).

H4: Perceived relevance acts as a mediator between AI-driven personalization and impulse buying behavior.

Rationale: The indirect effect of AI personalisation operates through the relevance gateway, as posited by Tam and Ho (2006) and recently reaffirmed by the SOBC model of Shamim and Misra (2025).

H5 (Exploratory): Age moderates the association between AI-driven personalization and Perceived Relevance, indicating that younger consumers are more sensitive.

Rationale: Gen Z and late Millennial consumers, characterised by digital nativity and habitual platform engagement, are more cognitively attuned to personalisation cues and have established deeper algorithmic trust relative to older cohorts (Iskandar, 2025; Wahdaniyah et al., 2025).

4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a quantitative, cross-sectional, explanatory research design. The explanatory orientation is appropriate because the central objective is not merely to describe the frequency of impulse purchasing among Indian online shoppers, but to establish and quantify the mechanisms through which AI personalisation influences purchasing behaviour. The cross-sectional design enables efficient, large-scale data collection within a defined temporal window, though its limitation for causal inference is acknowledged in Section 8.

4.2 Sampling and Data Collection

The target population consists of adults in India who have purchased from domestic e-commerce platforms (Amazon India, Flipkart, Myntra) at least once in the preceding six months. A convenience sampling design was adopted to administer a structured questionnaire through Google Forms by leveraging social media, email, and messaging platforms. Convenience sampling is appropriate for an exploratory-explanatory study of this nature, where the primary objective is to estimate path coefficients and test mediation mechanisms rather than to generate population-representative prevalence estimates (Hair et al., 2019).

After removing incomplete submissions and respondents who classified themselves as non-shoppers, the study retained 247 valid responses for the final usable sample. Cohen's (1992) power analysis for medium effect sizes ($f^2 = 0.15$) at $\alpha = .05$ with three predictors in the most complex regression equation indicates a minimum sample of 119 for 80% statistical power; the obtained sample of 247 exceeds this benchmark comfortably.

4.3 Measurement Instrument

The survey instrument consisted of four sections. Section I collected demographic information (age group, gender, online shopping frequency, active shopper status). Sections II–IV measured the three focal constructs using validated scales adapted for the Indian e-commerce context:

- AI-Based Personalisation (5 items): Adapted from Xu et al. (2011). Sample item: "The platform provides personalised product recommendations based on my past activity."
- Perceived Relevance (4 items): Adapted from Tam and Ho (2006). Sample item: "The recommended products match my current needs and interests."

- Impulse Buying Behaviour (5 items): Adapted from Rook and Fisher (1995). Sample item: "I feel a strong urge to buy when I see a personalised recommendation."

The items were administered on a five-point Likert scale, where 1 corresponded to Strongly Disagree and 5 corresponded to Strongly Agree. The scale wording was evaluated and minimally revised to ensure cultural and contextual appropriateness and to preserve the meaning of the construct, consistent with the standard adaptation procedure set out by Brislin (1970).

4.4 Analytical Framework

Data analysis was conducted in the following sequential stages:

a) **Reliability analysis:** internal consistency was evaluated using Cronbach's alpha (α), adopting the conventional criterion of ≥ 0.70 (Nunnally, 1978).

b) **Descriptive and correlation analysis:** means, standard deviations, and Pearson correlation coefficients (r) were calculated to describe the sample and to provide initial indications of associations among constructs.

c) **Path analysis implemented through OLS regression:** three separate OLS regression models were estimated to examine H1, H2, and H3, in accordance with the Baron and Kenny (1986) four-step mediation procedure. In this path-analytic framework, the proposed theoretical relationships are modelled as a set of hypothesised paths, with each β coefficient indicating the standardized path strength. Structural Equation Modelling (SEM) was considered as an alternative validation approach; however, given the study's sample size of 247 and its focus on a single mediator rather than a multi-construct latent-variable measurement model, the OLS-based Baron and Kenny (1986) procedure combined with the Sobel test was judged the more appropriate and statistically efficient choice for this stage of the research. SEM (specifically PLS-SEM) is identified in Section 8 as a priority direction for future replication with a larger, stratified sample.

d) **Sobel mediation test:** the statistical significance of the indirect effect (a × b) was examined with the Sobel test statistic, thereby providing a formal test of H4.

e) **Supplementary Group Analyses:** One-way ANOVA (shopping frequency × impulse buying), independent-samples t-test (gender × impulse buying), and age-based group comparisons were conducted to explore boundary conditions.

5. DATA ANALYSIS AND RESULTS

5.1 Demographic Profile of Respondents

Table 1. Demographic Profile of Respondents (N = 247)

Variable	Category	n	%
Age Group	18–25 (Gen Z)	195	79
	26–35	35	14
	36–40	6	2.4
	Above 40	6	2.4
	Below 18	5	2
Gender	Male	174	71
	Female	71	29
	Prefer not to say	2	0.8
Shopping Frequency	Rarely	52	21
	Occasionally	116	47
	Frequently	65	26
	Very Frequently	14	5.7
Active Online Shopper	Yes	236	96

The sample is disproportionately concentrated in the 18–25 age bracket (79.3%), reflecting the characteristic demographic profile of India's active e-commerce user base and the recruitment channels employed. The IBEF (2023) reports that consumers aged 18–35 account for approximately 65% of Indian e-commerce transactions by value, suggesting the sample, while not population-representative, is well-aligned with the commercially most significant consumer segment. The gender skew (70.7% male) is an acknowledged limitation that circumscribes the generalisability of gender-based comparisons.

It is also clarified that the five respondents below 18 were retained in the analytic sample because the survey did not apply a strict age-based eligibility filter, while the "Active Online Shopper" item was a separate self-reported behavioural measure of purchase frequency rather than a screening criterion; the 236 respondents so classified are therefore not a formal age-defined subset of the 247, and this distinction should be borne in mind when interpreting sample-wide results. Given that the study's stated target population is adult online shoppers, the inclusion of respondents below 18 is acknowledged here as a limitation of sample screening.

5.2 Reliability Analysis

Table 2. Cronbach's Alpha Reliability Coefficients (N = 247)

Construct	No. of Items	Cronbach's α	Interpretation
AI-Based Personalization	5	0.922	Excellent
Perceived Relevance	4	0.927	Excellent
Impulse Buying Behaviour	5	0.883	Excellent

All three constructs demonstrate excellent internal consistency, substantially exceeding Nunnally's (1978) minimum threshold of 0.70 and Hair et al.'s (2010) preferred threshold of 0.80 for confirmatory research. These alpha values indicate that the adapted survey items cohesively measure their respective constructs and that measurement error is unlikely to explain substantive variance in the regression results.

5.3 Pearson Correlation Analysis

Table 3. Pearson Correlation Matrix (N = 247)

Construct	(1) AI Personalisation	(2) Perceived Relevance	(3) Impulse Buying
(1) AI Personalisation	1	0.785***	0.487***
(2) Perceived Relevance	0.785***	1	0.598***
(3) Impulse Buying	0.487***	0.598***	1
Mean	3.54	3.42	2.97
SD	1	0.99	0.98

Note: *** $p < .001$ (two-tailed)

All bivariate correlations are positive and statistically significant ($p < .001$), providing preliminary support for H1–H3. The correlation between AI Personalisation and Perceived Relevance ($r = 0.785$) is the strongest in the matrix, establishing that the algorithm-relevance perception link is robust. The comparatively weaker correlation between AI Personalisation and Impulse Buying ($r = 0.487$ vs. $r = 0.598$ for Perceived Relevance–Impulse Buying) provides the structural signature of partial or full mediation: the distal stimulus-response relationship is weaker than the proximal mediator-response relationship, which is precisely what a mediation model predicts.

No correlation exceeds 0.85, suggesting multicollinearity is not a concern, a claim further supported by the sequential regression analysis below.

5.4 Path Analysis — Hypothesis Testing via OLS Regression

Table 4. Path Analysis Results for H1, H2, and H3 (N = 246–247)

Hyp.	Path	Predictor	Outcome	β	R^2	F	t	Result
H1	a	AI Personalization	Perceived Relevance	0.77	0.62	393.34***	19.83***	**Supported**
H2	b	Perceived Relevance	Impulse Buying	0.6	0.36	136.41***	11.68***	**Supported**
H3	c	AI Personalisation	Impulse Buying	0.48	0.24	76.26***	8.73***	**Supported**

Note: *** $p < .001$. β = standardised regression coefficient (path coefficient). R^2 = proportion of variance explained.

H1 is strongly supported: AI personalisation accounts for 61.6% of the variance in Perceived Relevance ($\beta = 0.772$, $p < .001$). This is a large effect size (Cohen, 1992) and confirms that the AI personalisation systems deployed by Indian e-commerce platforms are sufficiently sophisticated to produce a meaningful relevance experience in the majority of surveyed consumers. The magnitude of this path coefficient exceeds that reported in several comparable Western studies (e.g., Bleier & Eisenbeiss, 2015), potentially reflecting the higher daily exposure frequency of Indian e-commerce users or the relative novelty of algorithm-driven personalization in this market.

H2 is supported with a moderate effect: Perceived Relevance explains 35.8% of the variance in Impulse Buying ($\beta = 0.596$, $p < .001$). This confirms that the relevance appraisal is a powerful proximal predictor of spontaneous purchasing — when a recommendation resonates with the consumer's current self-concept and situational needs, the probability of an unplanned purchase increase substantially.

H3 is supported, but this direct path is the weakest in the model ($\beta = 0.477$, $R^2 = 0.237$). This anticipates the mediation finding: when examined in isolation, AI personalisation does predict impulse buying, but a substantial proportion of that relationship is attributable to indirect influence through relevance.

5.5 Mediation Analysis — Sobel Test for H4

Following the Baron and Kenny (1986) four-step procedure:

- Step 1 (Path a): AI Personalisation → Perceived Relevance: $a = 0.772$, $SE = 0.039$, $t = 19.833$, $p < .001$ ✓
- Step 2 (Path b, controlling for X): Perceived Relevance → Impulse Buying (controlling AI Personalisation): $b = 0.560$, $SE = 0.082$, $t = 6.829$, $p < .001$ ✓

- Step 3 (Total effect c): AI Personalisation → Impulse Buying: c = 0.477, p < .001 ✓
- Step 4 (Direct effect c′): AI Personalisation → Impulse Buying (controlling Perceived Relevance): c′ = 0.045, SE = 0.081, t = 0.559, p = .576 (non-significant) → Full Mediation

Table 5. Mediation Analysis — Sobel Test Results for H4 (N = 247)

Path	Coefficient	SE	t / z	p	Significance
Path a: AI Personalisation → Perceived Relevance	a = 0.772	0.039	t = 19.833	< .001	***
Path b: Perceived Relevance → Impulse Buying (controlling AI)	b = 0.560	0.082	t = 6.829	< .001	***
Total effect c: AI Personalisation → Impulse Buying	c = 0.477	0.055	t = 8.733	< .001	***
Direct effect c′: AI Personalisation → Impulse Buying (controlling PR)	c′ = 0.045	0.081	t = 0.559	0.576	n.s.
Indirect effect (a × b): Sobel Test	0.432	—	z = 6.421	< .001	**FULL MEDIATION**

Note: *** p < .001; n.s. = not significant

H4 is supported — Full Mediation is confirmed. The indirect effect (a × b = 0.772 × 0.560 = 0.432) is statistically significant (Sobel z = 6.421, p < .001), and the direct path c′ is non-significant (p = .576). This constitutes full mediation by the criteria of Baron and Kenny (1986), indicating that AI personalisation does not directly drive impulse buying when consumers are actively processing it; rather, its entire behavioural effect is channelled through the relevance appraisal.

This result has significant implications for business strategy: the return on investment from personalization spending depends entirely on how well the relevance experience is delivered to consumers. An AI system that is technically sophisticated but fails to produce a subjective relevance perception in the consumer will generate zero incremental impulse purchases. Conversely, a system that successfully operationalises relevance — through contextual cues, personalised framing, or culturally resonant product pairings — unlocks the full pathway to impulse purchase.

5.6 Summary of Hypothesis Testing

Table 6. Summary of All Hypotheses (N = 247)

Hyp.	Statement	Key Statistic	p-value	Result
H1	AI Personalisation → Perceived Relevance	$\beta = 0.772$, $R^2 = 0.616$, $t = 19.833$	< .001	**Supported**
H2	Perceived Relevance → Impulse Buying	$\beta = 0.596$, $R^2 = 0.358$, $t = 11.679$	< .001	**Supported**
H3	AI Personalisation → Impulse Buying (total)	$\beta = 0.477$, $R^2 = 0.237$, $t = 8.733$	< .001	**Supported**
H4	Perceived Relevance fully mediates H3 path	Indirect = 0.432, Sobel z = 6.421	< .001	**Supported (Full Mediation)**
H5	Age moderates AI Personalisation → Relevance	Exploratory group comparison (see 5.7.3)	—	**Directionally Consistent (Not Formally Tested)**

5.7 Supplementary Analyses

5.7.1 Shopping Frequency and Impulse Buying — One-Way ANOVA

Table 7. One-Way ANOVA — Shopping Frequency vs. Impulse Buying Behaviour

Shopping Frequency	n	IB Mean	SD	ANOVA Result
Rarely	52	2.91	0.9	
Occasionally	116	2.8	0.9	**F = 5.118**
Frequently	65	3.37	1	**p = .002****
Very Frequently	14	2.79	1.4	

The ANOVA reveals a significant overall effect of shopping frequency on impulse buying propensity ($F(3, 243) = 5.118$, $p = .002$). Frequent shoppers show the highest impulse buying mean ($M = 3.37$, $SD = 1.01$), significantly above both occasional ($M = 2.80$) and rare ($M = 2.91$) shoppers. This result aligns with the habituation-amplification mechanism reported by Rasool et al. (2025): habitual platform users develop more automated responses to personalisation cues, reducing the deliberative resistance that moderates impulse purchasing among occasional shoppers.

The counterintuitive finding that Very Frequent shoppers ($M = 2.79$) report lower impulse buying scores than Frequent shoppers warrants interpretation. The most parsimonious explanation is a saturation effect: consumers who shop with very high frequency develop greater familiarity with algorithmic patterns, becoming

desensitised to recommendation stimuli and more strategic in their purchase evaluations. This saturation hypothesis aligns with the filter bubble fatigue research (Pariser, 2011) and warrants formal examination in future studies.

5.7.2 Gender and Impulse Buying — Independent Samples t-Test

An independent-samples t-test found no statistically significant gender difference in impulse buying propensity (Female: M = 3.03, SD = 0.94; Male: M = 2.95, SD = 1.00; t = –0.555, p = .579). This null finding is substantively meaningful: the AI personalisation–impulse buying pathway appears to operate with comparable intensity across genders in this sample. Given the gender imbalance (70.7% male), this result should be interpreted cautiously but suggests that personalisation strategies need not be gender-differentiated at the mechanism level.

5.7.3 Age Group Comparison — Exploratory Analysis (H5)

Table 8. Age Group Comparisons on Key Constructs

Age Group	n	AI Personalisation Mean	Perceived Relevance Mean	Impulse Buying Mean
18–25 (Gen Z)	195	3.6	3.49	3.02
26–35	35	3.29	3.14	2.84
36+	17	3.18	3.07	2.68

Note: Means computed from construct composite scores (all items averaged). Full ANOVA-based moderation inference is not possible given unequal and small group sizes in older cohorts; these means are presented as exploratory comparisons.

The directional pattern is consistent with H5: as age increases, mean scores on all three constructs decline. The 18–25 cohort reports the highest AI personalisation perception (M = 3.60), the highest perceived relevance (M = 3.49), and the highest impulse buying propensity (M = 3.02). This finding is consistent with the perspective that digital nativity among Gen Z consumers strengthens algorithmic trust and increases sensitivity to relevance. Similarly, Iskandar (2025) concludes that, among Gen Z consumers, impulse purchases prompted by AI advertising personalization yield stronger effects even when usage frequency is held constant.

However, the restricted group sizes for the 26–35 (n = 35) and 36+ (n = 17) cohorts preclude statistically reliable moderation inference. Formal Age moderation testing would require minimum group sizes of 100+ per cohort for Multi-Group Analysis (MGA) in PLS-SEM, or sufficiently powered interaction terms in a moderated regression framework. This constitutes a methodological limitation of the present study and a direct recommendation for future research design.

6. DISCUSSION AND STRATEGIC IMPLICATIONS FOR CONTEMPORARY BUSINESSES

6.1 Theoretical Contributions

This study makes three distinct theoretical contributions to the literature on AI-driven consumer behavior.

First, it reaffirms and extends the primacy of Perceived Relevance as the operative mechanism through which AI personalisation influences impulse buying. The full mediation finding — the direct path from AI personalisation to impulse buying collapses entirely when Perceived Relevance is controlled — establishes that the algorithm's commercial potency is entirely contingent on the consumer's relevance appraisal. This has not been demonstrated with this level of statistical precision in the Indian e-commerce context, and it provides a tightly specified mechanism that can inform system design.

Second, the study empirically documents the "relevance variance ratio": AI personalisation accounts for 61.6% of the variance in Perceived Relevance (R^2 = 0.616), but Perceived Relevance accounts for only 35.8% of the variance in Impulse Buying (R^2 = 0.358). This asymmetry reveals that while AI personalisation is highly effective at generating relevance perceptions, the translation of relevance into impulse buying is subject to other moderating forces — potentially including mood, financial constraint, social norms, and the post-impulse regret mechanism identified by Rook and Fisher (1995). Future research should explicitly model these additional moderators.

Third, the study contributes to the growing body of work on the SOBC extension of S-O-R (Shamim & Misra, 2025) by demonstrating that the consequence dimension — specifically the risk of privacy concern activation — is a theoretically necessary complement to the behaviour stage. The personalisation-privacy paradox (Xu et al., 2011) remains operationally unresolved, and its implications for long-term brand loyalty constitute a consequence that the S-O-R model alone cannot fully represent.

6.2 Strategic Implications for Contemporary E-Commerce Businesses

The findings generate several concrete strategic mandates for e-commerce businesses operating in the AI-integrated retail landscape.

Invest in Relevance Quality, Not Recommendation Quantity. The mediation analysis indicates that, within this cross-sectional sample, the ROI of personalisation infrastructure is closely tied to subjective relevance perception rather than the volume of recommendations generated. Platforms that serve consumers with high-frequency low-relevance recommendations risk triggering reactance — a defensive cognitive response that reduces engagement rather than increasing it (Brehm & Brehm, 1981).

The strategic recommendation is to shift from recommendation volume optimisation toward relevance quality metrics, operationalised as consumer-rated relevance scores collected systematically through in-app feedback mechanisms.

Deploy Contextual and Temporal Personalisation. Ahmed et al. (2025) identify contextual relevance and delivery timing as the two strongest predictors of purchase intention in AI-driven marketing campaigns. Platforms should use contextual signals — such as device type, time of day, the context of a recent browsing session, seasonal micro-events, and location-based cues — to strengthen the perceived immediacy and relevance of recommendations. A product recommended during the browsing context in which it is most likely to feel relevant converts at substantially higher rates than the same product recommended out of context.

Operationalise Algorithmic Transparency. Lu et al. (2025) document that explaining the rationale behind a recommendation ("Recommended because you purchased X last month") increases both trust and relevance perception. This practice, known as explanation-based personalisation, converts the AI from an invisible and potentially unsettling influence into a visible and trustworthy collaborator in the shopping experience. Indian consumers who understand the DPDPA (2023) implications may be especially receptive to transparency cues like these.

Target the Frequent Shopper Segment Strategically. The ANOVA finding (Section 5.7.1) demonstrates that frequent shoppers exhibit the highest impulse buying propensity, while very frequent shoppers show a saturation effect. This suggests a strategically optimal window of maximum personalisation impact — consumers in the "frequently" bracket are sufficiently habituated to the platform to respond automatically to personalisation cues but not yet desensitised. Platforms should design loyalty programs, push notification schedules, and recommendation intensity levels that maintain consumers in this high-susceptibility window without triggering the saturation-induced drop observed in the "very frequently" group.

Design for the Gen Z Relevance Sensitivity Profile. The exploratory age analysis (Section 5.7.3) shows that the 18–25 cohort is not only more frequent users but more receptive to personalisation stimuli, recording higher means on all three constructs. This suggests that Gen Z-targeted platforms (e.g., Myntra, Meesho) should invest disproportionately in personalisation infrastructure quality, as the relevance-to-impulse translation rate is highest for this cohort. Conversely, platforms targeting older demographics (26+) may need to supplement personalisation with deliberative decision support tools — comparison features, expert reviews, and contextual value articulation — to compensate for the lower automatic relevance sensitivity observed in these groups.

6.3 Ethical Dimensions and Regulatory Compliance

The findings carry non-trivial ethical weight that contemporary businesses must integrate into their AI governance frameworks. The establishment of a full mediation pathway from AI personalisation through relevance to impulse buying is consistent with AI recommendation systems being associated with unplanned purchases, though the cross-sectional design means this pathway should be interpreted as a statistical association rather than definitive proof of causal instrumentality.

Several dimensions require explicit managerial attention:

The DPDPA (2023) Compliance Imperative. Under India's Digital Personal Data Protection Act, 2023, data principals can demand enforceable protections, including being informed about the use of their data and withdrawing consent for data processing. Personalization systems that collect and process behavioural data for impulse-triggering recommendation purposes must now operate within this regulatory framework. Businesses must audit their data processing pipelines for DPDPA compliance and ensure that consent mechanisms are genuine rather than procedural.

Algorithmic Nudging and Consumer Vulnerability. Haryanto et al. (2025) and Wahdaniyah et al. (2025) both identify emotional triggers — urgency, scarcity, FOMO — as amplifiers of the personalisation-impulse buying pathway. Using these mechanisms coercively against consumers under conditions of intense emotional distress, financial hardship, or compulsive shopping tendencies constitutes exploitation and places the parties involved at reputational, legal, and ethical risk. Responsible AI guidelines, such as those increasingly promoted by the Bureau of Indian Standards (BIS) and international frameworks like the EU AI Act, recommend that high-stakes behavioural nudges carry opt-out mechanisms and contextual warnings.

Long-Term Brand Loyalty vs. Short-Term Conversion. Shamim and Misra (2025) note that trust acts as a critical moderator of the loyalty consequences of AI-induced impulse buying — if consumers retrospectively attribute their impulse purchases to algorithmic manipulation rather than genuine desire, brand trust erodes. The implication is that maximising short-term impulse conversion without ensuring long-term relevance satisfaction creates a business model that cannibalises future loyalty. Sustainable commercial advantage requires that the relevance experience be genuine rather than manufactured through dark patterns.

7. CONCLUSION

This study aimed to explain how AI-driven personalization on Indian e-commerce platforms is associated with impulse buying, and to assess Perceived Relevance as the psychological mechanism mediating this relationship. The results are theoretically well supported and practically actionable.

Artificial intelligence personalization is a major commercial driver in today's Indian retail, though it does not act as a simple impulse trigger. Its ability to elicit spontaneous purchasing is entirely channeled through the consumer's subjective sense of relevance, the conviction that the algorithm understands what the consumer needs, when they need it. This complete mediation is not only an empirical finding; it also sets a strategic requirement. All return on investment from personalization spending passes through the relevance gateway, so firms that invest in the quality of the relevance experience - rather than the size, frequency, or technical sophistication of recommendations - will achieve better conversion results.

The findings further suggest that shopping frequency, but not gender, influences consumers' impulse-buying propensity, as evidenced by the 18–25 group showing the highest responsiveness to personalisation cues. These results align with a habituation-amplification mechanism among frequent shoppers and a digital native advantage for Gen Z consumers.

Looking ahead, there is a need for methodological refinement toward PLS-SEM, featuring bootstrapped indirect effects, longitudinal or clickstream-based behavioral validation, and formal moderation testing employing balanced age-group samples. The integration of Trust in AI, Emotional Engagement, and Privacy Concern as additional constructs within the SOBC framework would greatly strengthen the model. From a strategic perspective, generative artificial intelligence shopping assistants that enable natural-language discussions of consumer preferences point to a qualitative shift in the personalization paradigm that scholarly work has only begun to conceptualize.

This study concludes that the algorithmic impulse is not a technological artifact, but a psychological one. Companies that recognize this difference and invest accordingly will shape the next phase of Indian retail.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study is subject to several well-recognised constraints. The cross-sectional design prevents causal inferences; although the mediation analysis confirms the structural relationships anticipated by theory, longitudinal or experimental designs would yield stronger causal evidence. The sample is demographically concentrated (79.3% aged 18–25; 70.7% male), which restricts generalisability to older and more gender-balanced consumer groups. This concentration is compounded by the use of convenience sampling: because respondents were recruited through the researchers' own social media, email, and messaging networks rather than through probability-based methods, the sample may not adequately represent the broader population of Indian online shoppers, and findings should be generalised with caution. Because key measures rely on self-report, social desirability bias is likely, especially for impulse-buying items with normative implications. Although common method bias was

reduced through the construct-level analysis, it was not formally tested using Harman's single-factor test or via a marker variable approach.

Future research should prioritise the following: (1) replication using a balanced, stratified sample to enable formal Multi-Group Analysis (MGA) by age cohort; (2) extending the model by adding Trust in AI as a competing or complementary mediator and treating Privacy Concerns as a theoretically grounded moderator; (3) moving to PLS-SEM with SmartPLS 4, with complete reporting of the measurement model outputs (CR, AVE, HTMT ratios) and bootstrapped indirect effects; (4) incorporating actual behavioural data (clickstream and transaction records) from e-commerce platform APIs to validate self-reported impulse buying against real purchase behaviour; and (5) cross-national replication to assess whether the full mediation finding extends beyond the Indian market.

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