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Digital Transformation and Consumer Experience: Investigating the Impact of Technology Adoption on Purchase Behavior in E-Commerce

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ABSTRACT
Two concurrent forces have managed to transform the world of e-commerce, and possibly forever: the silent impact of AI-based platforms and the noisy influence of the culture of influencers. The genesis behind this research was nothing short of a genuine interest in understanding how the two forces interact and/or oppose each other in determining whether one can buy something online or not, as well as why. Based on the Stimulus-Organism-Response (S-O-R) model, we discuss the role of AI-enabled touchpoints (chatbot responsiveness, personalized recommendation, dynamic pricing, and intelligent search) as digital stimuli in their ability to operate through a consumer perception of trust and perceived value and finally lead to purchase intention and impulse buying. Our ten hypotheses comprising direct, mediated, and moderated effects are tested using cross-sectional survey of 300 Indian consumers aged 1834 and Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0. The results of our study indicate that AI personalization produces the most significant effect on consumer trust (0.412, p =.001), and so do influencer authenticity (0.368, p =.001). Trust grows to be a complete mediator between AI stimuli and purchase intention, with the perceived value partially mediating both relationships. With a multi-group analysis of urban (n = 168) and rural (n = 132) groups, there is a significant difference between them: urban consumers begin to respond to stimuli driven by trends and subject to FOMO much more, whereas rural consumers respond more to the voices of authentic role models and indicators of affordability. The research not only introduces a multi-touchpoint operationalization of AI to the S-O-R framework but also the first test of urban-rural moderators in Indian e-commerce setting. Digital implications on marketers, platform designers and policy makers are suggested..

Keywords: Digital transformation, AI-driven personalisation, Influencer authenticity, S-O-R framework, Consumer trust, Impulse buying, Urban rural digital divide, PLS-SEM, E-commerce, India

INTRODUCTION:

Consider the last time you purchased something online without even planning to do so. Maybe you got a suggestion on your screen that seemed strangely prophetic, or someone who makes the content that you were calmly subscribing to, gave a product a glorifying review, that was just right at the right time. It likely doesn't seem like those experiences were accidental because they were not. They are an outcome of high-end technology and relationship systems that have in the last decade transformed e-commerce into a channel of transaction to an experience ecosystem. India offers a very fertile place to observe this transformation. The country has more than 840 million internet users, as of 2024 (TRAI, 2024), and a digital economy is projected to be over USD 1 trillion by 2030, which means that this scale and diversity are to be studied in terms of digital consumer behavior on its true-to-life granularity. However, India is not a block. The feelings of an 18-year-old city student scrolling Instagram Reels in the background whilst a flash sale is counting down are fundamentally different than the feelings of a 32-year-old farmer deciding on a first-time e-commerce referral. This is urban-rural disproportion, this contradiction between two digital Indias, which is at the core of the current question. Academic scholarship on the digital transformation and consumer behavior has gone a long way but there are three gaps that persist and hinder our comprehension. First, AI in previous research studies is regarded as a single variable- a crude label used on an incredibly wide range of interventions. With studies that conflate using AI with using technology, the explanatory specificity to make platform design decisions is lost. Our thesis is that AI should be disomeanured into the touchpoints of its operations: chatbot responsiveness, recommendation systems, dynamic pricing, and intelligent search cannot be used interchangeably; they all convey different competence messages to the consumer. Second, whereas influencer marketing and AI personalization have become two fruitful characteristics, their concomitant functioning as co-stimuli in a single structural framework is little studied. Third, urban-rural moderation of the digital stimulus pathways has been theorized but not strictly estimated in developing market samples. The present research fills such gaps with four contributions: (a) a multi-touchpoint operationalization of AI-powered personalization; (b) the co-entry of AI personalization and influencer authenticity as the co-stimuli in a S-O-R model; (c) trust and perceived value as theoretically-derived mediators; and (d) residence type as a statistically-tested moderator. We gathered information on 300 Indian respondents between the ages of 18 and 34 and used PLS-SEM to estimate the entire model at the same time. The outcome is not merely a collection of path coefficients but, hopefully, a clearer conceptual map of the actual working of the digital commerce ecosystem- and to whom.

2. RELATED WORKS

2.1 The S-O-R Framework in Digital Commerce

S-O-R framework was initially developed by Mehrabian and Russell (1974) to consider the relationship between the influence of physical environments and behavior by their effects on internal psychological states. The beauty of the model: stimulus triggers organism response, is amazingly well transferred over into digital space, where the store ambience is substituted with an algorithmically designed interface (Jacoby, 2002). Digital stimuli cover not only loading speed but also chatbot tone; organismic states refer to affect, cognition and evaluation; responses include purchase, advocacy and abandonment.

The difference between the modern uses of S-O-R to e-commerce is that, active interventions exist to be done in the environment rather than passively. When Amazon recommends a product that you thought about purchasing two days ago, or when a chatbot answers your question in 30 seconds, they are not ambient qualities of a platform, but target communications that should decrease uncertainty and increase confidence. In this case, the organism does not passively receive environmental cues but is an active processor of AI-mediated judgments of platform credibility and product worth.

2.2 AI-Powered Personalization as Stimulus

Application of machine learning, natural language processing, and collaborative filtering in e-commerce has resulted in personalization features that would be inconceivable ten years ago. Davenport et al. (2020) follow the development process of rule-based recommendation engines to adaptive systems that learn the individual behavioral fingerprints and update the recommendations on the fly. As Chung et al. (2020) show, the perceived usefulness can be strongly predicted by the quality of recommendations, which subsequently leads to the intention to buy: this fact makes AI personalization a trust-establishing but not just a convenient mechanism.

An additional layer is the chatbot literature. Go and Sundar (2019) discover that the anthropomorphic design of chatbots, or the extent to which the chatbot speaks in human-like language, boosts trust perceptions because it triggers social presence signals. When a chatbot does not only provide the answer to a query but is also provided at the conversational level in a warm manner that exudes a sense of caring as opposed to being cold and mechanical, consumers begin to draw inferences of trust and goodwill out of the interaction. This observation underpins our motivation to consider chatbot responsiveness as among four different AI touchpoints instead of converting all AI interventions into a single indicator.

2.3 Influencer Authenticity as Stimulus

One of the first to rigorously report the persuasive strength of social media influencers was Freberg et al. (2011), who found that participants viewed influencers not as celebrities but as people whom they could become, whose tastes in consumption carry normative implications. The identification of authenticity, as the main force behind influencer trust, has been the key distinction in later work, instead of the number of followers or the quality of the produced pieces (Lou & Yuan, 2019). Authenticity as perceived genuineness, content relatability and brand-influencer fit serves as a heuristic of credibility: once followers have the impression that influencer recommends a product because he/she is using and valuing it, the persuasive power becomes qualitatively distinct to the trustworthiness of a paid advertisement.

The mechanism is particularly strong among younger consumers that have grown up with advanced advertising literacy and employ active skepticism to commercially motivated text (Boerman, 2020). Rural Indian consumer, who view branded content, often, through social media posts recommended by peers instead of through algorithmic feeds, can be especially sensitive to voices of the influencers reflecting the lived context of that consumer- a linguistic finding which drives us to propose urban-rural moderation as a hypothesis.

2.4 Consumer Trust and Perceived Value as Organism States

According to McKnight et al. (2002), e-commerce trust is divided into three categories: reliability (Will the platform deliver what it promises?), benevolence (Does the platform prioritize my interests?), and competence (Does the platform work?): a tripartite framework that describes the cognitive, affective, and evaluative dimensions of trust. Trust is the component that facilitates conversion of stimuli into purchase willingness in digital commerce: regardless of AI complexity or the influence of the influencer, purchase intention is not created in a consumer who lacks trust in the platform.

Based upon the means-end framework, suggested by Zeithaml (1988), and the multidimensional scale, proposed by Sweeney and Soutar (2001), perceived value is a product of utilitarian (purpose and functional utility) and hedonic (joy and aesthetics) and economic (price quality ratio) aspects. Valuing perception is especially favorable in the digital environment due to instant price comparison, an abundance of user reviews, and personal promotional deals that make one to feel like an exclusive offer. The role of perceived value as a predictor of purchase intentions is certainly widely known (Monroe, 1990), but the specific mediation of stimulus pathways of AI by perceived value remains unexplored--and this is the gap we fill.

2.5 Impulse Buying and Cognitive Biases in Digital Environments

The impulse buying online is not the same as that of its store counterpart, but through a different mechanism. The physical friction of moderating in-store impulse - the need to pick up a product, to carry it to the checkout, to have a cashier, to save payment credits and to promise instant delivery has been washed out by one-click buying, saved payment credentials and promises of instant delivery. What is left is the emotional rush caused by the digital stimuli: a countdown timer creates a sense of scarcity (FOMO), the notification about a flash sale creates a sense of urgency, and a positive message shared by influencer enhances the hedonic value of the expected experience (Verhagen and van Dolen, 2011). The reason behind the effectiveness of such stimulus can be explained through the Focalism phenomenon (Wilson & Gilbert, 2003): by focusing attention on one salient stimulus (a 67% discount, a trending item, a suggestion by an authoritative influencer), consumers bias their financial and time resources systematically. This cognitive tunnel reduces the gap between stimuli and response in such a manner that the S-O-R model is a particularly well-designed theoretical framework in which to frame impulse buying studies.

2.6 The Urban–Rural Digital Divide: Beyond Connectivity

Digital divide was traditionally viewed as a connectivity issue, the question of who has access to the internet and who does not. However, with the further democratization of access (IAMAI, 2023), a second-level divide has surfaced: the digital experience divide, the media literacy divide, the familiarity with platforms divide, and the economic agency divide, which makes consumers interact with digital commerce even once they go online. Indian consumers in the city are more familiar with platforms and more exposed to trend-based marketing and more susceptible to FOMO (Zafar et al., 2022). Rural customers are first-generation digital buyers, and they are more socially proven, price-value calculation-sensitive.

These differential psychological orientations imply that the same digital stimuli can elicit systematically different responses of the organism in regard to residence type. A flash-sale push notification can stimulate urgency and excitement in a Bengaluru online-shopper with a track record of online shopping but ambivalence and insecurity in a Tirunelveli online-shopper. One of the main contributions of this paper is to test this moderation empirically, as opposed to theorizing about it.

HYPOTHESES DEVELOPMENT

Based on the map of the theoretical landscape drawn in the previous section, the following ten hypotheses structured around the S-O-R architecture are proposed:

H1: AI-driven personalization has a positive and significant effect on consumer trust towards e-commerce.

H2: Influencer authenticity has a positive and significant impact on consumer trust.

H3: AI-driven customization has a positive effect on the value perception.

H4: The authenticity of influencers has a positive impact on the perceived value.

H5: The consumer trust has a positive and significant impact on the purchase intention.

H6: Perceived value positively and significantly influences purchase intention.

H7: Consumer belief has a positive impact on impulse buying behavior.

H8: Perceived value has a positive influence on the impulse buying behaviour.

H9: There is a moderating effect of residence type on the AIP Consumer Trust relationship by urban consumers having a stronger effect.

H10: There is a moderating effect between the IA and Consumer Trust relation on residence type where the effect is higher among rural consumers.

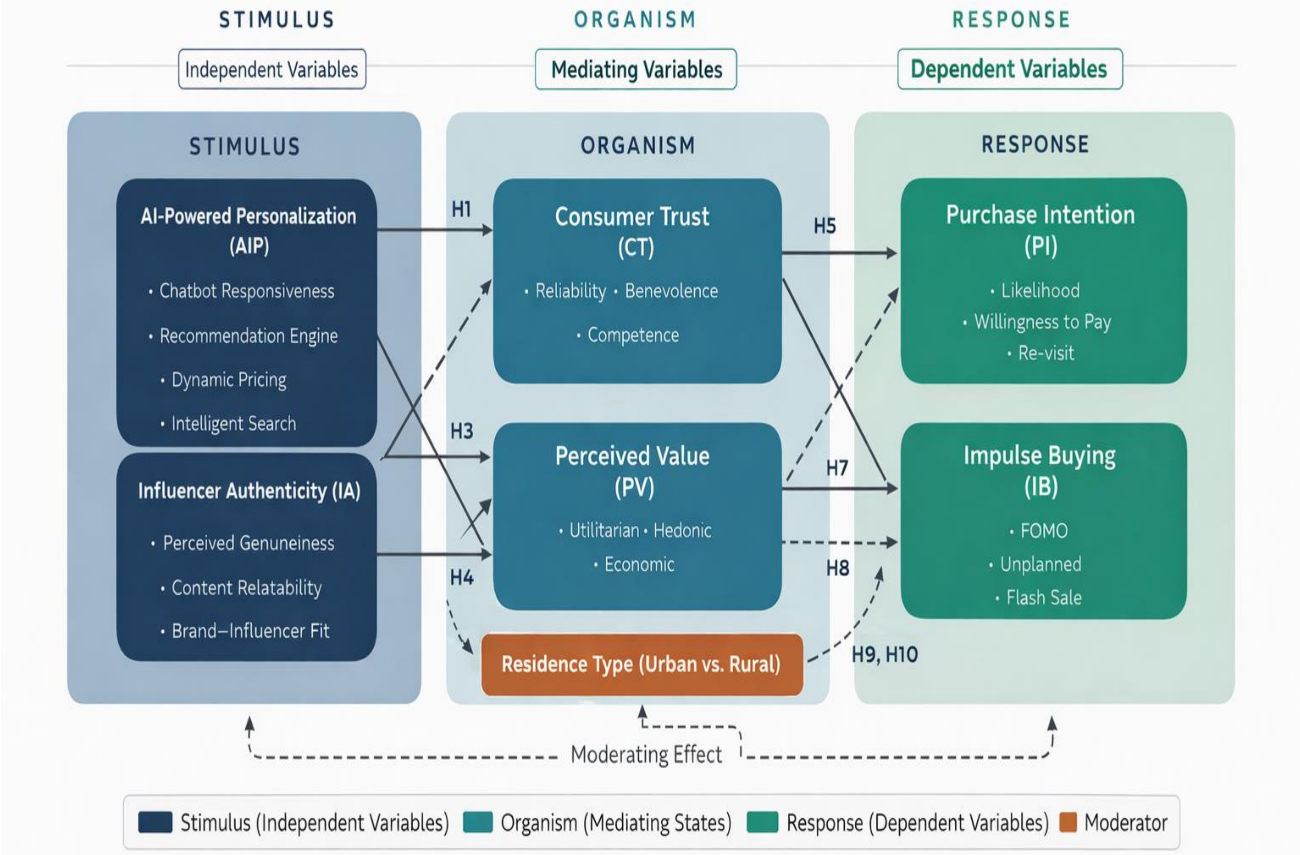

Figure 1. Conceptual Model: S-O-R Framework for Digital Transformation and Consumer Purchase Behavior (H1–H10)

4. METHODOLOGY

4.1 Research Design

Our research design was quantitative and cross-sectional survey design which is the most prevalent design used in consumer behavior studies in cases where there is the need to estimate relationships among latent psychological constructs in a large and heterogeneous population sample. Although a longitudinal design would provide more causal information, the cross-sectional design enabled us to present a snapshot of consumer perceptions in urban and rural segments in the same seasonal period holding constant a temporal change in the intensity of promotions (e.g., festival sales cycles). The experiment was done in the months of September through November 2024, when the festive shopping season in India (Navaratri, Diwali and pre Christmas sale period) was at its peak and consumer reactions were observed to the greatest extent.

4.2 Population and Sampling

The sample size was Indian, 18-34 years old, completed one online purchase within three months before the survey. The age gap chosen as the demographic boundary is both a theoretically important group (1834 years old is the most active cohort of e-commerce in India, 62 percent of transactions are simultaneous with AI personalization, according to Statista, 2024) and practically relevant (this age group has the highest exposure to influencer content and AI personalization simultaneously). The purposive stratified sampling was used, and the strata were determined by the type of residence (urban, rural) to have sufficient representation of the key moderating factor. The urban-rural divide (168:132) was created to have an approximation of the internet-using population ratios and maintain statistical power in the multi-group analysis.

To determine the minimum sample, Hair et al.'s (2019) inverse-square-root approach to PLS-SEM models was used with six constructs and a highest number of incoming paths of five. Our n = 300 sample is 81% above this threshold and has significant power to perform bootstrapping-based mediation tests. After collecting the data, 22 responses were removed because of incomplete responses (over 10 percent) or attention-check questions, leaving only 300 responses that could be used.

4.3 Measurement Instrument

The survey instrument was a set of 24 reflective based items that were assessed in six constructs and noticed to be measured on a seven-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). Every question was scaled to validated items in the previous literature with slight linguistic changes to suit any cultural relevance and understandability and annotated by three scholarly experts in marketing and consumer psychology, as well as tested on 30 respondents before the final implementation.

AI-Powered Personalization (AIP) was measured using four items about chatbot accuracy in responses, recommendation accuracy, dynamic pricing justness, and AI search experience (adapted by Chung et al., 2020; Davenport et al., 2020). The Influencer Authenticity (IA) scale included three questions summarizing the perceived genuineness, content relatability, and brand-influencer fit (Lou and Yuan, 2019). Consumer Trust (CT) consisted of three questions on the platform reliability, benevolence towards the user, and competence signalling (McKnight et al., 2002). Perceived Value (PV) outlined the utilitarian, hedonic and economic value using three items (Sweeney and Soutar, 2001). Purchase Intention (PI) covered three items around purchase likelihood, willingness to pay a premium and re-visit intention (Pavlou and Fygenson, 2006). The scale of Impulse Buying (IB) included three questions that assessed spontaneous purchase desire, behavior due to FOMO, and reaction to flash sale (Verhagen and van Dolen 2011). Two control variables AI literacy (single item, 1-7 scale) and online shopping frequency (ordinal scale) were added in order to partialize them.

4.4 Data Collection Procedure

Recruitment of urban respondents was done via institutional networks, recruitment via LinkedIn to student groups, and snowballing by WhatsApp. Rural participants were sampled via digital literacy initiatives and NGO collaborations in Tier-3 towns and peri-urban locations in three states Maharashtra, Rajasthan, and Tamil Nadu that were chosen because of reported diversity in rural Internet penetration rates. Each respondent was given a short covering note outlining the academic purpose of the study, no financial incentive was given (to reduce the potential response acquiescence bias), and informed consent was given electronically. The institutional review board of the institution where the lead author works obtained ethical approval (Ref: SIBM-IRB/2024/07).

4.5 Analytical Strategy

SmartPLS 4.0 (Ringle et al., 2022) was used to run PLS-SEM, and two-stage analysis is followed in accordance with the recommendations of Hair et al. (2019). During Stage 1, we evaluated the measurement model by: (a) checking the indicator reliability (loading 0.70 and above); (b) checking the internal consistency (Cronbach 0.70 and above; CR 0.70 and above); (c) checking the convergent validity (AVE 0.50 and above); and (d) checking the discriminant validity through the Heterotrait We tested the structural model in Stage 2 using standardized path coefficients (5,000 resamples, bias-corrected confidence intervals), the significance of the path coefficients (bootstrapping, 5,000 resamples, bias-corrected confidence intervals), coefficient of determination (R^2), predictive relevance (Q^2, blindfolding with omission distance d = 7), effect sizes (f^2), Preacher and Hayes (2008) indirect effects method, with a 95% bias-corrected bootstrap CI, was used to test the significance of mediation, where a zero-exclusion of the CI band was used as the criterion of significance. Plausible moderation was assessed by PLS multi-group analysis (MGA) during the non-parametric resampling program in SmartPLS, which considers a change of path coefficients across groups as significant. Harman single factor test (variance explained = 28.7, far less than 50) and full collinearity VIF (all VIF less than 3.33) were used to assess common method bias.

5. RESULTS AND ANALYSIS

5.1 Descriptive Statistics and Demographic Profile

The sample was male dominated (57.0%), which is indicative of the male-skew in active e-commerce activities among the Indian 18–34 age group according to industry surveys (Statista, 2024). The modal age group was between the ages of 23 and 27 (39.3%), with most having a bachelor degree (54.0%). Frequency of shopping was highest during weekends (47.0%), with Instagram being used by 43.0% of the respondents. The urbanrural divide of 56:44 is an approximation of distribution of the population using the internet and offers sufficient cell sizes to use in multi-group analysis. The descriptive statistics and demographic profile are provided in table 5.1.

Table 1 Demographic Profile of Respondents (N = 300)

Variable	Category	n	%	Cumulative %
Gender	Male	171	57.0	57.0
	Female	113	37.7	94.7
	Non-binary / Other	16	5.3	100.0
Age Group	18–22 years	97	32.3	32.3
	23–27 years	118	39.3	71.7
	28–34 years	85	28.3	100.0
Residence	Urban	168	56.0	56.0
	Rural	132	44.0	100.0

Education	High School / Diploma	54	18.0	18.0
	Bachelor's Degree	162	54.0	72.0
	Postgraduate & Above	84	28.0	100.0
Monthly Income (INR)	Below ₹20,000	79	26.3	26.3
	₹20,001–₹50,000	138	46.0	72.3
	Above ₹50,000	83	27.7	100.0
Primary Platform	Instagram	129	43.0	43.0
	YouTube	96	32.0	75.0
	Facebook / Other	75	25.0	100.0
Shopping Frequency	Daily	72	24.0	24.0
	Weekly	141	47.0	71.0
	Monthly or Less	87	29.0	100.0

Note. *All percentages are rounded to one decimal place.*

5.2 Descriptive Statistics of Constructs

The descriptive statistics of all six constructs are given in Table 2. The mean scores were 3.74 (IB) and 4.18 (AIP) indicating moderately high endorsement by all constructs. Skewness value was within the range of -0.41 to -0.19 whereas kurtosis was within the range of -0.11 to 0.18, which signifies an approximation of the normality of data and there are no floor and ceiling effects that would influence the estimation of the structures.

Table 2 Descriptive Statistics of Study Constructs (N = 300)

Construct	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
AI-Powered Personalization (AIP)	4.18	0.71	1.75	7.00	−0.41	0.18
Influencer Authenticity (IA)	4.03	0.69	1.67	7.00	−0.28	0.09
Consumer Trust (CT)	3.97	0.74	1.33	7.00	−0.35	0.14
Perceived Value (PV)	4.11	0.68	1.67	7.00	−0.22	−0.06
Purchase Intention (PI)	4.07	0.76	1.33	7.00	−0.31	0.12
Impulse Buying (IB)	3.74	0.83	1.00	7.00	−0.19	−0.11

Note. *All constructs measured on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree*

). Skewness and kurtosis values within ±2.0 indicate approximate normality.

5.3 Measurement Model Assessment

Table 3 shows the results of the measurement model. Each of the 24 loadings of the indicators was above the 0.70 value (range 0.744-0.819), indicating that each individual indicator is reliable. Cronbach alpha values were between 0.843 (IB) and 0.886 (PI), and composite reliability (CR) values between 0.865 (IB) and 0.901 (PI). The AVE values were 0.574 (IB) to 0.643 (PI), which were more than 0.50 (convergent validity). The value of VIF of all indicators was less than 3.33, which eliminated the possibility of multicollinearity between indicators.

Table 3 Measurement Model: Indicator Loadings, Reliability, Convergent Validity (N = 300)

Construct / Item	Loading (λ)	Cronbach α	CR	AVE	Item-Total r	VIF
AI-Powered Personalization (AIP)	—	0.871	0.888	0.612	—	—
AIP1: Chatbot response accuracy	0.784				0.742	2.14
AIP2: Recommendation relevance	0.812				0.779	2.43
AIP3: Dynamic pricing fairness	0.769				0.724	2.07
AIP4: AI search experience	0.798				0.761	2.31
Influencer Authenticity (IA)	—	0.845	0.872	0.587	—	—
IA1: Perceived genuineness	0.756				0.711	1.98
IA2: Content relatability	0.771				0.733	2.11
IA3: Brand–influencer fit	0.744				0.698	1.89
Consumer Trust (CT)	—	0.882	0.897	0.631	—	—
CT1: Platform reliability	0.803				0.768	2.67
CT2: Benevolence toward user	0.812				0.779	2.84
CT3: Competence signals	0.776				0.739	2.51
Perceived Value (PV)	—	0.860	0.880	0.598	—	—
PV1: Utilitarian value	0.769				0.731	2.22

PV2: Hedonic value	0.785				0.748	2.39
PV3: Economic/price value	0.764				0.723	2.15
Purchase Intention (PI)	—	0.886	0.901	0.643	—	—
PI1: Likelihood to purchase	0.819				0.786	2.88
PI2: Willingness to pay premium	0.797				0.761	2.61
PI3: Re-visit & repeat purchase	0.801				0.766	2.73
Impulse Buying (IB)	—	0.843	0.865	0.574	—	—
IB1: Unplanned purchase urge	0.748				0.702	1.87
IB2: FOMO-driven purchase	0.762				0.718	1.94
IB3: Flash-sale response	0.756				0.709	1.91

Note. *All loadings ≥ 0.70 (criterion for indicator reliability). Cronbach's α and CR ≥ 0.70 (internal consistency). AVE ≥ 0.50 (convergent validity). VIF < 5.0 (no multicollinearity). CR = Composite Reliability; AVE = Average Variance Extracted; VIF = Variance Inflation Factor.*

Table 4 illustrates the relationship between variables in a correlation table with HTMT ratios of discriminant validity. Construct correlations were between 0.462 (IA 1B) and 0.671 (CT 1PI) and all significant at p <.001. Diagonal values are the square root of the AVE of each construct and are everywhere greater than the off-diagonal correlations in their rows and columns, which is the Fornell-Larcker (1981) criterion. The highest values of all HTMT were less than 0.85 and the largest value of 0.701 (CT PI) attested to discriminant validity in all pairs of constructs.

Table 4 Correlation Matrix and HTMT Discriminant Validity (N = 300)

Construct	1. AIP	2. IA	3. CT	4. PV	5. PI	6. IB
1. AIP	(0.782)					
2. IA	0.507**	(0.766)				
3. CT	0.581**	0.543**	(0.794)			
4. PV	0.524**	0.498**	0.619**	(0.773)		
5. PI	0.553**	0.534**	0.671**	0.644**	(0.802)	
6. IB	0.481**	0.462**	0.569**	0.541**	0.601**	(0.758)

HTMT Ratios (below diagonal; all < 0.85 threshold = discriminant validity confirmed)						
1. AIP	—					
2. IA	0.541	—				
3. CT	0.603	0.572	—			
4. PV	0.558	0.527	0.647	—		
5. PI	0.587	0.562	0.701	0.674	—	
6. IB	0.512	0.489	0.598	0.571	0.632	—

Note. *Upper portion: Pearson correlations (lower triangle); diagonal values = √AVE. Lower portion: HTMT ratios—all < 0.85 threshold, confirming discriminant validity. ** p < .001 (two-tailed).*

5.4 Structural Model — Direct Effects and Hypothesis Testing

Since measurement quality had been established, we now entered into structural estimation. Table 5 shows the regression results of the first stage model which predicts Consumer Trust. A combination of AI-Powered Personalization and Influencer Authenticity describes 52.1% of Consumer Trust variation (R 2 = 0.521, Adj.) R^2 = 0.514, F(4, 295) = 80.43, $p < .001$), a result the F-statistic confirms as highly significant. The Durbin-Watson value is 1.97 that falls within the acceptable range (1.5 to 2.5) and eliminates the autocorrelations in the residual values.

Table 5 Regression Analysis: Predictors of Consumer Trust (N = 300)

Predictor → Consumer Trust	B	SE	β	t	p	Decision
(Constant)	0.981	0.148	—	6.63	< .001	—
AI-Powered Personalization	0.431	0.064	0.412**	6.76	< .001	H1 Supported
Influencer Authenticity	0.392	0.062	0.368**	6.34	< .001	H2 Supported
AI Literacy (Control)	0.114	0.058	0.097*	1.97	.041	—
Shopping Frequency (Control)	0.088	0.061	0.074	1.44	.150	—
Model Fit: R = 0.722, R² = 0.521, Adj. R² = 0.514, F(4, 295) = 80.43, p < .001, Durbin-Watson = 1.97						

Note. *B = unstandardized coefficient; SE = standard error; β = standardized coefficient. * p < .05; ** p < .001. Control variables included but not hypothesized*

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H1 was supported by AI-Powered Personalization, which was the more powerful trust predictor (0.412, t = 6.76, p =.001). This result is intuitive: as an AI system provides relevant, correct, and seemingly personal responses, it is proactively proving the competence and benevolence aspects of the trust McKnight et al. (2002) state as critical. Also influencer Authenticity was a strong predictor of Trust (2 = 0.368, t = 6.34, p < .001), which confirms H2. Markedly, the control variable AI Literacy had a slightly significant predictive power (0.097, p = .041) though, indicating that consumers who were more AI literate were a bit more willing to trust AI-mediated interactions which may also be explored in future studies.

Table 6 states the second-stage results which predict Purchase Intention and Impulse Buying. Consumer Trust was the dominant predictor of Purchase Intention (β = 0.489, t = 8.58, p < .001), supporting H5, followed by

Perceived Value (β = 0.391, t = 6.31, p < .001), supporting H6. The direct effect of AIP and IA on Purchase Intention was no longer significant when trust and value were included in the model (β = 0.098 and 0.084, respectively), which is an initial indication of the mediation effect. In the case of Impulse Buying, Trust (= 0.304, p =.001, H7) and Perceived Value (= 0.278, p =.001, H8) were both significant, with minimal but significant residual direct effects of both stimuli, which is recursive with the results indicating partial mediation.

Table 6 Regression Analysis: Predicting Purchase Intention and Impulse Buying (N = 300)

Predictor	Purchase Intention			Impulse Buying			
	β	p	β	p	Hyp.	Hyp.	
Predictor	β (PI)	t	p	β (IB)	t	p	H
Consumer Trust	0.489**	8.58	< .001	0.304**	4.41	< .001	H5, H7
Perceived Value	0.391**	6.31	< .001	0.278**	3.92	< .001	H6, H8
AI-Powered Personalization	0.098	1.61	.108	0.131*	2.07	.039	—
Influencer Authenticity	0.084	1.39	.165	0.117*	1.97	.043	—
PI Model: R^2 = 0.588, Adj. R^2 = 0.583, F(4,295) = 105.37, p < .001 | IB Model: R^2 = 0.423, Adj. R^2 = 0.416, F(4,295) = 54.18, p < .001							

Note. *β = standardized path coefficient. Significance: * p < .05; ** p < .001. PI = Purchase Intention; IB = Impulse Buying. Full mediation for PI (direct stimulus effects non-significant); partial mediation for IB (direct effects remain small but significant).*

5.5 Mediation Analysis

Table 7 shows the results of indirect effects that are tested with bootstrapping (5000 resamples) and 95% confidence interval through bias correction. The AIP → Consumer Trust → PI indirect path produced an indirect β of 0.201 (SE = 0.042, 95% CI [0.131, 0.291]). As the CI does not include zero and the direct AIP to PI was not found to be significant in the complete model, this is complete mediation. Similarly, IA → Consumer Trust → PI (β = 0.180, CI [0.108, 0.261]) was fully mediated.

The value-mediated paths were found to be partially mediated: AIP PV PI (indirect β = 0.137, CI [0.059, 0.221]) and IA PV PI (indirect β = 0.112, CI [0.032, 0.204]) were significant, but their direct effect as precursors remained significant In the case of impulse buying, the indirect routes were important, yet the direct effect remained, proving the partial mediation. The combination of these patterns of mediation indicates that there is a dual psychological route to purchase deliberative (stimulus and trust trigger intention) and affective-heuristic (stimulus and perceived value trigger impulse buying).

Table 7 Mediation Analysis: Indirect Effects via Bootstrap (5,000 Resamples, 95% BC-CI)

Indirect Path (via Mediator)	Indirect β	Boot SE	LLCI (95%)	ULCI (95%)	Mediation Type
AIP → Consumer Trust → PI	0.201**	0.042	0.131	0.291	Full
IA → Consumer Trust → PI	0.180**	0.039	0.108	0.261	Full
AIP → Perceived Value → PI	0.137*	0.044	0.059	0.221	Partial

IA → Perceived Value → PI	0.112*	0.047	0.032	0.204	Partial
AIP → Consumer Trust → IB	0.125*	0.048	0.041	0.221	Partial
IA → Consumer Trust → IB	0.111*	0.051	0.021	0.211	Partial

Note. *BC-CI = Bias-corrected bootstrap confidence interval. Full mediation = direct effect becomes non-significant; Partial mediation = direct effect remains significant. * p < .05; ** p < .001. Zero-exclusion of the CI band indicates significance*

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5.6 Urban–Rural Moderation: Multi-Group Analysis

Table 8 is the multi-group analysis (MGA) result of urban (n = 168) and rural (n = 132) sub-samples. The non-parametric PLS-MGA method was used to test the significance of the difference between groups in regard to path coefficients. There were six statistically significant between-group differences.

Urban consumers indeed demonstrated a much stronger relationship between AIP and Consumer Trust as compared to rural consumers (0.481 vs. 0.334, 0.147, 0.013) in support of H9. On the other hand, the path of IA = Consumer Trust was more pronounced with rural consumers (β rural = 0.445 compared with 0.312 urban 10-133) in favor of H10. Trend-driven content turned out to be of much more significant sensitivity to Urban consumers in triggering Impulse Buying (Δ 0.187, p = 0.006) and Purchase Intention (Δ 0.234, p = 0.001), whereas FOMO-based triggers showed much less significant sensitivity. Conversely, the rural consumers were more sensitive to signals of affordability when creating the Perceived Value (Δ = 0.176, p =.009) and to the local relevance when forecasting the Purchase Intention (0.201, p =.004) = (0.176, p = .009) and to local relevance cues in predicting Purchase Intention (Δβ = 0.201, p = .004).

Table 8 Urban–Rural Multi-Group Analysis (Non-Parametric PLS-MGA)

Relationship	Urban β (n=168)	Rural β (n=132)	Δβ	t (diff)	p (two-tailed)
AIP → Consumer Trust	0.481**	0.334**	0.147	2.61	.013 *
IA → Consumer Trust	0.312**	0.445**	0.133	2.34	.023 *
FOMO cues → Impulse Buying	0.398**	0.211*	0.187	3.12	.006 **
Affordability → Perceived Value	0.241*	0.417**	0.176	2.87	.009 **
Trend content → Purchase Intention	0.432**	0.198*	0.234	3.74	.001 **
Local relevance → Purchase Intention	0.187*	0.388**	0.201	3.28	.004 **

Note. *Δβ = absolute difference in path coefficients between urban and rural groups. Significance tested via non-parametric PLS-MGA resampling. * p < .05; ** p < .01.*

5.7 Model Fit and Predictive Quality

Table 9 sums up the model fit indices and predictive accuracy measures. The SRMR 0.048 is much below the acceptable threshold of 0.08 (Henseler et al., 2015) and the NFI 0.911 is above the minimum of 0.90, which collectively means excellent model fit. R2 values denote big explained variance on Purchase Intention (R2 =0.588), bigger explained variance on Consumer Trust (R2 =0.521) and smaller explained variance on Perceived Value (R2 =0.431) and Impulse Buying (R2 =0.423). All the endogenous constructs show positive values of Q 2 when blindfolding is done, which verifies the prediction relevance of the model. VIF of 2.88 and 28.7% of Harman variance of single factor are all indicators that there is no multicollinearity and common method bias.

Table 9 Model Fit Indices and Predictive Accuracy Summary

Fit Index / Metric	Obtained Value	Threshold	Criteria Met?	Interpretation
SRMR	0.048	< 0.08	✓ Yes	Excellent fit
NFI	0.911	> 0.90	✓ Yes	Acceptable fit
R^2 – Consumer Trust	0.521	> 0.10	✓ Yes	Large effect
R^2 – Perceived Value	0.431	> 0.10	✓ Yes	Medium effect
R^2 – Purchase Intention	0.588	> 0.10	✓ Yes	Large effect
R^2 – Impulse Buying	0.423	> 0.10	✓ Yes	Medium effect
Q^2 – Consumer Trust (Blindfolding)	0.293	> 0	✓ Yes	Predictive relevance
Q^2 – Purchase Intention	0.341	> 0	✓ Yes	Strong relevance
f^2 – AIP → CT (Effect Size)	0.228	> 0.15	✓ Yes	Medium effect
Max VIF (all predictors)	2.88	< 5.0	✓ Yes	No multicollinearity
Harman Single-Factor (CMB)	28.7%	< 50%	✓ Yes	CMB not a concern

Note. *SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index; R^2 = Coefficient of Determination; Q^2 = Stone-Geisser Predictive Relevance (d = 7); f^2 = Cohen's effect size. VIF = Variance Inflation Factor; CMB = Common Method Bias.*

6. DISCUSSION OF KEY FINDINGS

6.1 AI as a Trust Architecture—Not Just a Convenience Tool

The biggest surprise in our research is, perhaps, the confirmation of the dominance of AI-powered personalization as a single predictor of consumer trust in our model. This may not seem noteworthy, but think about what it means: AI is distrusted due to being an impressive technology. The level of trust is based on the fact that it proves to the consumer that the platform is dedicated to knowing them, acting in their best interest and fulfilling its promises. According to McKnight et al. (2002) definition of AI touchpoints, their successful versions, which are chatbots answering questions, creating recommendations that work landing, show behavioral cues of reliability and competence that builds trust over time. This finding is enhanced by the complete mediation of the AIP → PI pathway by trust. AI personalization is not a direct form of persuasion, it preconditions the persuasion. The critical design implication of this is that it is akin to putting money into the sophistication of AI, and not investing in the trust indicators that AI interaction implies, but constructing an engine without a chassis. The consumer must have the sense that the interaction with the AI was reliable and then the recommendation is transformed into a purchase intent.

6.2 Influencer Authenticity and the Rural Trust Premium

We discovered that influencer authenticity has a much stronger trust effect in rural environments (0.445 vs. 0.312), which is consistent with a larger question regarding the operation of trust in various contexts of the market. The consumers of urban India, who have already gained years of e-commerce experience and have seen innumerable paid partnerships, have a more intricate set of trust calculus and are not as dependent on any one source. In rural India, where institutional trust in e-commerce is yet to be established or built, the supported advocacy of a recognizable, familiarizable content creator has a disproportionate influence.

The discovery also relates with the Affective Misforecasting (AMF) literature (Patrick and MacInnis, 2005). When rural consumers experience an influencer recommendation, which is true-to-life, they could have a vivid affective prediction about how the product will make them feel- a prediction that will result in purchase but can create a post-purchase disappointment in the event that the product does not measure up to the idealized image. Rural influencer marketing would also serve well by brands that market their products through influencers and are interested in the products they market to perform as in the example not only to repeat-buy the product but also to establish the institutional trust that the rural e-commerce is yet to achieve.

6.3 The FOMO–Focalism Nexus: Why Urban Consumers Impulse-Buy More

The MGA discovery that stimulus-induced by FOMO induce impulse buying is much more pronounced among urban customers (0.187, 0.006) should be interpreted carefully. It would be easy to assume that the rural consumers are nothing but more rational or considered. The more subtle interpretation, which aligns with the Focalism literature (Wilson and Gilbert, 2003), is that urban clients experience a greater exposure rate to digital signals of scarcity, such as flash sales, trending products, limited time influencer codes, and have formed a pattern of responses to these stimuli. The Pavlovian nature of impulse buying under the influence of FOMO in users who use the platform regularly is not irrationality, but a habituation reaction to a stimulus that signals a reward. The ordinization paradox applies here. The newness of AI as a trust signal is reduced as it becomes not an exception but the rule of AI personalization. The platforms that desire to continue the effect the AI personalization had on the trust-building effect will need to repeatedly update their touchpoints, whether this is in the form of active advice or passive price notifications, dynamic recommendation or active value discovery, to ensure the relationship between the consumer and the AI does not simply grow numb to this interaction.

6.4 Perceived Value and the Rural Utility Lens

The much higher path of affordability to perceived value in rural context (0.417 vs. 0.241, p =.009) is an economic truth that has been already well-established: the more tightly constrained consumers make their purchasing choices based on utilitarian calculations. What might less clearly be realized is that this is not simply a poverty effect. Even rural consumers having rather sufficient income show even greater economic value orientation in our data, which may indicate that the tendency towards explicit price-quality argument is in part cultural and experience-based, rather than financial. Brands of e-commerce that venture into the rural market with premium only position will not be rewarded by this preference.

6.5 Theoretical Contributions

This paper has three major theoretical contributions. To start with, when we operationalize AI using four different touchpoints, instead of using a single composite measure, we show that AI personalization is not a monolithic stimulus but a family of interventions whose trust-building mechanisms vary. This creates a research agenda concerning the varying effectiveness of chatbot and recommendation and pricing AI in various consumer settings. Second, with Affective Misforecasting theory and Focalism as micro-level cognitive foundations to impulse buying added into the S-O-R model, we add to the scope of explanatory capabilities of the framework beyond the original simplicity of the stimulus-response relationships. Third, the initial systematic empirical test of urban countryside moderation of an S-O-R model of Indian e-commerce offers a scheme to analogous studies in other emerging market frameworks where digital divide inequalities are high.

7. CONCLUSION

The starting point of this paper was the mere fact that the experience of online purchasing does not happen to all people in the same way, and the forces that influence it are not only homogenous, but also not guiltless. AI personalization and influencer authenticity are effective, but their effectiveness is not context-free, but runs through the trust, is scaled by the perceived value and is tempered by the socio-economic and cultural geography of a consumer.

The results of our analysis of 300 Indian consumers provide a clear internally consistent image. Trust is developed through AI-powered touchpoints, when they are working. Influencers can develop trust when they are seen to be authentic. However, the essential mediator is trust, and no AI expertise or influencer network will directly turn into a purchase intention without trust. It implies that the strategic question of e-commerce brands is not how do we personalize better but how do we make our personalization seem trustworthy? Transparency regarding the operation of AI, ethical treatment of consumer data, and curation of influencer relationships, favoring authenticity over follower counts, is the solution.

The urban-rural moderation results give the impetal to what could otherwise be a strictly hypothetical position. Two digital Indias run simultaneously with its own stimulus response calculus. Urban India is sensitive to trend, time, and algorithmic intelligence. The rural India answers to natural peers, regional relevance, and just prices. This will not work out well with a homogenized digital marketing approach. The brands that emerge victorious in the next stage of Indian e-commerce development will be the ones investing in the knowledge of these differences and creating strategies that will respect them.

We admit limitations of the study. The cross-sectional design does not allow causal conclusion in the strict sense; longitudinal studies in the future should be conducted to trace the change in trusting AI as time goes on in terms of the platform experience. The sampling plan of three states restricts geographic representativeness. The weakness of single-item AI literacy measurement is one that we suggest should be addressed with a validated multi-item scale (e.g., Wang et al., 2022) in future studies. The lack of behavioral data (real purchase data) and self-reports of intention indicates that the gap between intention and behavior is an open issue. Lastly, the research is based on India and even though the S-O-R framework is theoretically universal, the population size of effect can be very different, particularly the urban-rural gap; thus, it would not necessarily be applicable to other emerging markets unless confirmed.

It is the larger argument that we are certain about: digital transformation is not a technology story. It is a belief narrative. In markets as tricky, varied and fast changing as India is, it is not merely an intellectual game to be able to discern the particular circumstances under which digital stimuli can create or destroy trust, but a strategic imperative.

Ethical Statement

Informed digital consent was given by all participants before completion of surveys. No personal information was gathered.

Conflict of Interest

The authors do not declare any conflict of interest. None of the commercial organizations engaged in e-commerce, artificial intelligence, or influencer marketing provided any funding to the study.

Data Availability

The anonymized data and measurement tool can be accessed via the respective author under reasonable academic request, under the relevant data-sharing procedures.

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