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AI Personalization and Trust Formation in E-Commerce: Examining the Role of Experiential Mediators and the Privacy Paradox

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ABSTRACT

As artificial intelligence (AI) becomes central to e-commerce strategy, how algorithmic personalization translates into consumer trust remains contested. Drawing on the Stimulus-Organism-Response (S-O-R) framework, the Technology Acceptance Model (TAM), and Privacy Calculus Theory, this study tests Satisfaction and Engagement as parallel experiential mediators and Privacy Concerns as a boundary condition among 130 "digital-native" e-commerce users (aged 18–35) in India. Using hierarchical regression and percentile bootstrap mediation (5,000 resamples), AI personalization predicted trust in isolation ($R^2 = .111$, $p < .001$) but became non-significant once Satisfaction and Engagement entered the model ($R^2 = .340$, $p < .001$), supporting full mediation (total indirect effect B = 0.45, 95% CI [0.23, 0.63], $p < .001$). The Engagement pathway was robust (B = 0.20, 95% CI [0.10, 0.33], $p < .001$); the Satisfaction pathway was only marginal (B = 0.25, 95% CI [−0.01, 0.43], $p = .064$), making Engagement the more dependable mediator. Privacy Concerns showed no significant relationship with Trust ($r = -.133$, $p = .131$), evidencing a privacy paradox in which functional utility outweighs perceived data risk. The study extends TAM by identifying an "experiential bridge" for AI-driven trust formation and offers managers a roadmap privileging experience design—especially engagement—over algorithmic sophistication.

Keywords: AI personalization, consumer trust, satisfaction, engagement, privacy paradox, e-commerce, digital natives, mediation analysis.

INTRODUCTION

Background and Problem Statement

The rapid evolution of artificial intelligence (AI) has fundamentally reshaped global e-commerce. Beyond simple transactional interfaces, major online retailers such as Amazon, Flipkart, and Myntra now deploy sophisticated algorithms to curate individualized shopping journeys, tailoring product recommendations, search results, and marketing messages to user-level data (Jeong et al. 2022). For "digital natives"—consumers aged 18–35 who have matured alongside ubiquitous connectivity—personalized interaction is no longer a differentiator but a baseline expectation (McKee et al. 2023). This demographic's high technological fluency and preference for efficiency lead it to rely on AI to reduce information overload and streamline decision-making (Kelly et al. 2023). Yet as AI systems deepen their integration into daily commerce, the consumer–platform relationship shifts from a purely functional exchange toward one anchored in the psychological construct of trust.

Despite widespread AI adoption, how automated personalization translates into durable consumer trust remains poorly understood. Many platforms implicitly assume that algorithmic accuracy directly produces trust; however, emerging evidence suggests trust is better characterized as an experiential outcome than as a direct product of technological capability. Prior work has predominantly tested the direct effect of personalization on trust without examining the psychological process—an "experiential bridge" of Satisfaction and Engagement—

through which this influence may actually operate (Jeong et al. 2022; Guo et al. 2022). This gap is compounded by a second, unresolved tension: AI personalization requires extensive data collection, which triggers Privacy Concerns (Ric and Benazić 2022). Whether these concerns meaningfully suppress trust, or are discounted by consumers who prioritize convenience—the so-called "privacy paradox"—remains actively debated, with findings diverging sharply across contexts: McKee et al. (2023) find that Gen Z consumers' privacy–benefit trade-offs strongly shape brand-avoidance behavior, whereas other work suggests the paradox dissolves once outcomes are measured as generalized platform trust rather than specific avoidance intentions. This study addresses both gaps using data from young Indian e-commerce consumers, testing whether AI personalization's effect on trust is mediated by Satisfaction and Engagement, and whether Privacy Concerns constitute a genuine barrier to or are overridden in trust formation.

Research Objectives

To address the problem stated above, this study pursues the following objectives:

1. To evaluate the direct influence of AI personalization on consumer trust in e-commerce platforms among digital natives (aged 18–35).
2. To examine the extent to which Satisfaction and Engagement act as mediating mechanisms in the relationship between AI personalization and consumer trust.
3. To investigate the impact of Privacy Concerns on trust formation and determine whether a "privacy paradox" exists within the target demographic.
4. To establish whether AI personalization requires experiential outcomes (Satisfaction and Engagement) to generate long-term platform trust.

Significance of the Study

This study contributes to theory and practice by clarifying the psychological mechanism through which AI personalization builds consumer trust, offering e-commerce managers an evidence-based basis for prioritizing experience design, and providing context-specific evidence on the privacy paradox from an underrepresented population of young Indian digital natives.

Scope of the Study

The study focuses exclusively on consumers aged 18 to 35, the most active segment of the Indian e-commerce market. The variables are limited to AI Personalization, Satisfaction, Engagement, Privacy Concerns, and Trust. Data reflect the perceptions of users interacting with general e-commerce platforms and may not generalize to specialized sectors such as fintech or health-tech.

LITERATURE REVIEW

Theoretical Foundation: Technology Acceptance and AI

Research on AI personalization is rooted primarily in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which position perceived usefulness as the primary driver of technology adoption. In e-commerce, AI personalization is theorized to enhance perceived usefulness by reducing information overload. However, a recent systematic review of AI-acceptance determinants (Kelly et al. 2023) finds that the factors driving acceptance vary considerably by context and technology type—a heterogeneity that cautions against assuming a uniform, direct path from algorithmic competence to trust. This inconsistency is precisely the gap the present study's mediation model is designed to address: rather than treating perceived usefulness as sufficient on its own, the study tests whether usefulness must first be converted into affective and behavioral experience (satisfaction, engagement) before it manifests as trust.

AI Personalization and Consumer Trust

Trust is conventionally defined as the consumer's willingness to be vulnerable to an e-commerce platform based on the expectation that it will perform as promised. Early research suggested a direct link between personalization accuracy and trust. More recent work complicates this view: Jeong et al. (2022), applying the Stimulus-Organism-Response (S-O-R) framework to real-world e-commerce recommendation data, found that personalized recommendations act as an effective behavioral stimulus, but the organism-level psychological response—not the stimulus itself—determines downstream outcomes. Similarly, Guo et al. (2022) demonstrate, in a non-AI service context, that customer behavioral intention is driven not directly by service stimuli but through the multiple mediating effects of service climate and engagement. Recent evidence corroborates this experiential-mediation logic outside the Indian context as well: in a 2025 SEM study of AI-driven e-commerce, personalized recommendations strengthened the trust–satisfaction–loyalty chain rather than driving loyalty directly, with satisfaction partially mediating the trust–loyalty link (El-Shihy, Hassan, and Abdelraouf 2025). Taken together, these studies suggest that the direct-effect assumption embedded in early personalization–trust research is increasingly untenable, and that trust is better modeled as the downstream product of an intervening experiential process—a proposition this study tests directly in the AI personalization context, where such mediation evidence remains scarce.

The Mediating Roles of Satisfaction and Engagement

A recurring theme in e-commerce literature is a Satisfaction–Engagement–Trust chain. Satisfaction is typically defined as the post-consumption evaluative judgment that occurs when an algorithm's recommendation matches the user's actual preference. Engagement is the behavioral manifestation of a customer's relationship with a brand. Evidence for these constructs as sequential “bridges” rather than parallel outcomes comes from cross-domain S-O-R applications: Ric and Benazić (2022) show, in a social-commerce setting, that interactivity stimulates purchase behavior only via an intervening motivational state, while Guo et al. (2022) report multiple, partially overlapping mediation paths rather than a single dominant one. This body of work supports treating Satisfaction and Engagement as parallel, non-redundant mediators—the modeling choice adopted here—rather than as a single composite “experience” variable, since the two constructs need not move in lockstep across contexts.

Privacy Concerns and the “Privacy Paradox”

The “dark side” of AI personalization is its dependence on data collection intensive enough to produce a “creepiness factor,” in which highly accurate AI makes consumers feel surveilled. Historically, the literature assumed high privacy concern would translate more or less linearly into low trust. Recent evidence complicates this assumption considerably. McKee et al. (2023), in a large Gen Z sample, identify a “privacy–benefits paradox” in which consumers simultaneously value personalization and resent the data practices that enable it, and find that this tension strongly predicts intentions to avoid brands perceived as under-personalizing or over-personalizing. This tension has since been formalized as a 'transformative privacy calculus,' in which consumers' broader emotional relationship with digital environments — not privacy concern in isolation — shapes how personalization benefits and privacy costs are weighed (Cloarec, Meyer-Waarden, and Munzel 2024), lending further support to treating generalized platform trust as distinct from situational privacy reactions. At first glance, this appears to conflict with the non-significant privacy–trust relationship this study anticipates; however, the two findings are reconcilable once the dependent variables are distinguished: McKee et al. model specific brand-avoidance behavior, a construct sensitive to salient, situational privacy violations, whereas the present study models generalized platform trust, a more diffuse and slower-moving evaluation. It is plausible—and this study tests—that privacy concerns shape narrow behavioral reactions without necessarily eroding the broader trust digital natives place in platforms whose personalization they have come to expect and value.

The Digital Native Perspective (Age 18–35)

Younger consumers exhibit a psychological profile distinct from older generations: greater “algorithmic awareness,” higher expectations for seamless personalized journeys, and a documented willingness to exchange personal data for convenience and relevance (Kelly et al. 2023; McKee et al. 2023). This group is simultaneously the most receptive to AI-driven personalization and the quickest to disengage if personalization feels irrelevant—underscoring why Satisfaction and Engagement, rather than personalization accuracy alone, are the theoretically appropriate proximal predictors of trust in this population.

Research Gaps

The literature review identifies three primary gaps that this study addresses:

1. The Mediation Gap: Most AI-personalization studies test direct effects; comparatively few examine the experiential bridge (Satisfaction and Engagement) that this study investigates using bootstrapped mediation analysis.
2. The Paradox Gap: Findings on how privacy concerns affect AI-enabled trust are inconsistent across dependent variables and populations (cf. McKee et al. 2023), warranting context-specific empirical resolution.
3. The Demographic Gap: There is a continuing need for localized data on Indian digital natives' trust-formation processes in e-commerce, a population underrepresented in the predominantly Western and East Asian samples that dominate this literature.

Research Hypotheses

To address the gaps identified above, the following hypotheses are proposed.

H1: AI Personalization has a significant positive effect on Consumer Trust.

H2: AI Personalization has a significant positive effect on User Satisfaction.

H3: AI Personalization has a significant positive effect on User Engagement.

H4: User Satisfaction has a significant positive effect on Consumer Trust.

H5: User Engagement has a significant positive effect on Consumer Trust.

H6: User Satisfaction significantly mediates the relationship between AI Personalization and Consumer Trust.

H7: User Engagement significantly mediates the relationship between AI Personalization and Consumer Trust.

H8: Privacy Concerns have a significant negative effect on Consumer Trust.

THEORETICAL FRAMEWORK

The rapid integration of AI in e-commerce has fundamentally transformed how firms interact with consumers, particularly through personalized recommendations and adaptive interfaces. To explain how AI-driven personalization influences consumer trust, this study draws on three complementary theoretical perspectives: the Stimulus–Organism–Response (S-O-R) model, the Technology Acceptance Model (TAM), and Privacy Calculus Theory.

The S-O-R model provides the foundational logic for the mediation hypotheses: external stimuli (S) influence internal cognitive and affective states (O), which subsequently shape behavioral responses (R). In e-commerce, AI-driven personalization functions as the stimulus, tailoring product recommendations and interfaces to individual preferences; these interactions shape consumers' internal states—Satisfaction and Engagement—which represent the organism component; these experiential states, in turn, determine trust, the response. Recent empirical S-O-R applications in e-commerce and social-commerce settings corroborate this staged logic: personalized stimuli affect purchase and loyalty outcomes only through intervening organismic states, not directly (Jeong et al. 2022; Guo et al. 2022; Ric and Benazić 2022). The present study is the first, to our knowledge, to apply this staged S-O-R logic specifically to AI-personalization-driven trust formation rather than to purchase intention or loyalty outcomes, which is where the bulk of existing S-O-R e-commerce evidence has concentrated.

TAM explains how users evaluate and adopt technological systems, positing perceived usefulness and perceived ease of use as key determinants of acceptance. In AI-enabled e-commerce, personalization enhances perceived

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usefulness by delivering relevant, timely recommendations, while adaptive interfaces reduce cognitive effort. However, as Kelly et al.'s (2023) systematic review demonstrates, the factors that translate perceived usefulness into downstream trust and continued use are neither uniform nor fully specified across contexts—reinforcing the need for the experiential mediators this study proposes as the missing conversion mechanism.

Privacy Calculus Theory addresses the trade-off AI personalization imposes: individuals weigh the benefits of disclosure (convenience, relevance) against its costs (data misuse, intrusion). This trade-off produces the privacy paradox, in which consumers express concern about privacy yet continue to engage with personalized services (McKee et al. 2023). In this study, Privacy Concerns are incorporated as a boundary condition that may negatively influence trust independent of, and potentially in tension with, the benefits derived from personalization.

Integrating these three perspectives, the study proposes that AI personalization influences trust indirectly through Satisfaction and Engagement (S-O-R mechanism), while being shaped by users' evaluations of technological benefit (TAM) and privacy-related trade-offs (Privacy Calculus). This integrative framework addresses the interplay between technological innovation and consumer psychology that single-theory models cannot fully capture.

METHODOLOGY

Research Design

This study employs a quantitative, cross-sectional research design to investigate the impact of AI personalization on consumer trust. A deductive approach was used, testing hypotheses derived from technology-acceptance and privacy-paradox theory. The study focuses on consumers aged 18 to 35—“digital natives” who interact most frequently with AI-driven e-commerce platforms.

Participants and Sampling

The final sample consisted of N = 130 respondents, all within the target age range (18–35). A purposive sampling technique was used, in which participation was restricted to individuals who self-identified as regular online shoppers within the target age band; data were collected via an online structured questionnaire distributed through digital consumer panels and social media platforms. Informed consent was obtained from all participants before data collection. Consent was obtained in written form through the online survey interface before respondents proceeded to complete the questionnaire.

A sample of this size is consistent with recommended minimum thresholds for regression-based mediation analysis with up to five latent constructs and a small number of predictors per path (Hair et al. 2022), and exceeds the N > 104 + m rule of thumb (where m is the number of predictors) commonly applied to multiple-regression-based hypothesis testing. The demographic profile of the sample is reported in Table 1.

As Table 1 shows, the sample was almost evenly split by gender (50.8% female, 49.2% male) and skewed toward lower-to-middle income bands, with 71.5% of respondents reporting a monthly income at or below ₹40,000—consistent with a sample drawn predominantly from students and early-career professionals within the 18–35 digital-native age range. Respondents were also experienced online shoppers: 65.4% reported at least four years of online shopping experience, though shopping frequency skewed toward occasional rather than habitual use (50.0% “occasionally,” only 3.1% “very frequently”), a profile consistent with deliberate, considered rather than reflexive engagement with AI-personalized features.

Table 1.Demographic and Respondent Profile (N = 130)

Characteristic	Category	n	%
Gender	Male	64	49.2
	Female	66	50.8
Monthly Income	Less than ₹20,000	45	34.6

	₹20,001–₹40,000	48	36.9
	₹40,001–₹60,000	18	13.8
	₹60,001–₹80,000	4	3.1
	Above ₹80,000	15	11.5
Online Shopping Experience	Less than 1 year	20	15.4
	1–3 years	25	19.2
	4–6 years	52	40.0
	7 years and above	33	25.4
Shopping Frequency	Rarely	39	30.0
	Occasionally	65	50.0
	Frequently	22	16.9
	Very Frequently	4	3.1

Note. Percentages within a characteristic sum to 100.0% (± 0.1 due to rounding). Age is not reported as a separate categorical breakdown because participation was restricted at the sampling stage to the 18–35 age band rather than measured as a continuous or banded survey item (see §1.4, Scope of the Study).

Reliability analyzes showed that all constructs (AP, SAT, ENG, PRIV, and TR) demonstrated high internal consistency, with Cronbach's Alpha values ranging from .83 (AI Personalization and Trust) to .90 (Privacy Concerns), exceeding the recommended .70 threshold (Hair et al. 2022).

Measurement Instruments

The survey instrument comprised five constructs adapted from validated e-commerce scales, each measured with four items on a 5-point Likert scale (“Strongly Disagree” to “Strongly Agree”): AI Personalization (AP), Satisfaction (SAT), Engagement (ENG), Privacy Concerns (PRIV), and Trust (TR). Construct scores used in all analyzes below are the mean of each construct's four items.

Data Analysis Procedure

Data analysis followed a multi-stage process consistent with current best-practice guidance for regression-based mediation (Hayes 2022) and structural equation modeling (Hair et al. 2022):

1. Reliability Testing: Cronbach's Alpha was calculated for each construct.
2. Descriptive Statistics: Frequencies and percentages profiled the sample's demographic characteristics.
3. Correlation Analysis: Pearson's r examined bivariate relationships among constructs.
4. Multiple Regression: Hierarchical linear regression tested the predictive power of AI Personalization, Satisfaction, Engagement, and Privacy Concerns on Trust.
5. Mediation Analysis: A percentile bootstrap mediation analysis (5,000 resamples) was conducted using the product-of-coefficients method to test the full-mediation hypothesis.

CONCEPTUAL FRAMEWORK

The research model as shown in Figure 1 posits that AI Personalization (independent variable) influences Trust (dependent variable) through the parallel mediators of Satisfaction and Engagement, while Privacy Concerns act as an independent predictor of trust formation. The paths tested are: AP → SAT, AP → ENG, SAT → TR, ENG → TR, PRIV → TR, and the residual direct path AP → TR. Standardized path coefficients for the finalized model, drawn directly from Table 2 and Table 3.2, are as follows: AP → SAT, $\beta = .71$ ($p < .001$); AP → ENG, $\beta = .56$ ($p < .001$); SAT → TR, $\beta = .38$ ($p = .001$); ENG → TR, $\beta = .39$ ($p < .001$); PRIV → TR, $\beta = -.04$ ($p = .554$); and the residual direct path AP → TR, $\beta = -.19$ ($p = .078$).

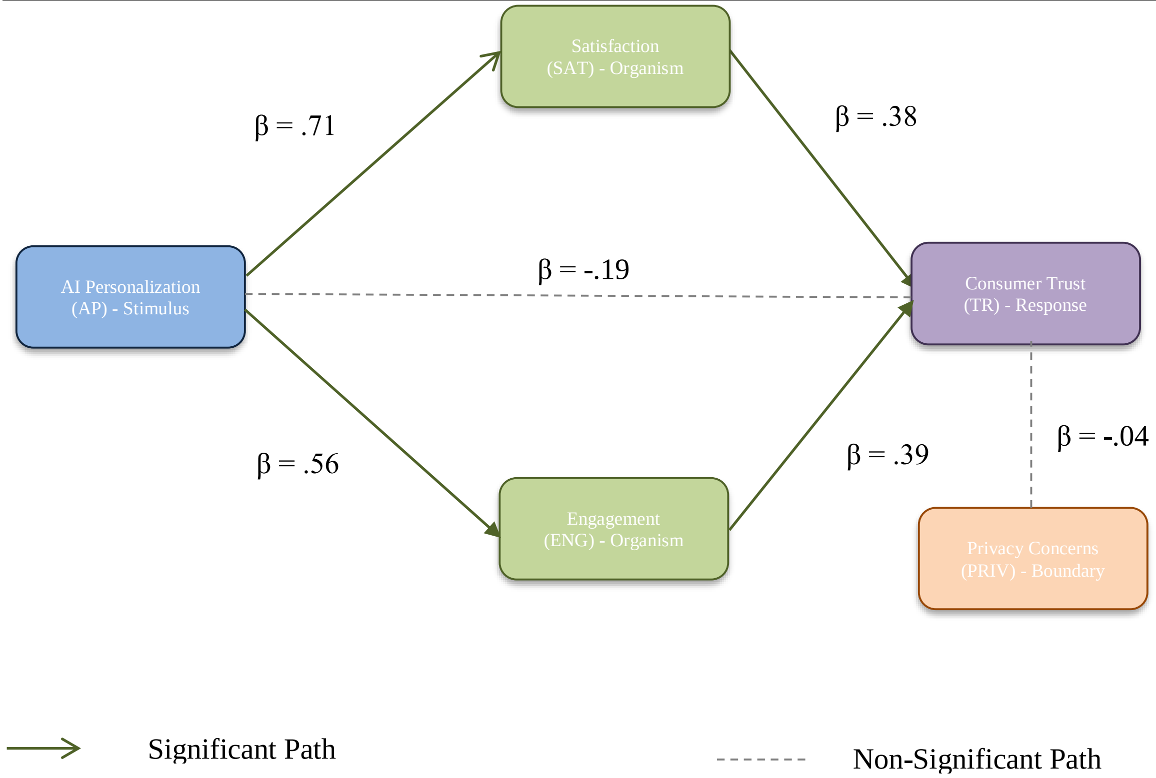

Figure 1. Conceptual Model

RESULTS

Preliminary Analyzes and Respondent Profile

The final sample consisted of N = 130 respondents, all within the target demographic of consumers aged 18–35. Descriptive statistics summarized Gender and Monthly Income to profile this digital-native group (Table 1, §4.2). Reliability analyzes showed that all constructs (AP, SAT, ENG, PRIV, and TR) demonstrated high internal consistency, with Cronbach's Alpha values ranging from .83 to .90, exceeding the recommended .70 threshold (Hair et al. 2022).

Bivariate Correlations and the Privacy Paradox

Pearson correlation coefficients assessed the strength and direction of relationships and evaluated potential multicollinearity. All intercorrelations among the four predictor constructs were below .80 (the highest, AP–SAT, was r = .71), indicating no multicollinearity concerns among the five constructs (Table 2).

Table 2.Means, Standard Deviations, and Intercorrelations Among Study Variables (N = 130)

Variable	1	2	3	4	5
1. AP	—				
2. SAT	.713***	—			
3. ENG	.557***	.619***	—		
4. PRIV	.090	−.020	−.162	—	
5. TR	.292**	.484***	.527***	−.133	—

Note. AP = AI Personalization; SAT = Satisfaction; ENG = Engagement; PRIV = Privacy Concerns; TR = Trust. M (SD): AP = 3.58 (0.89); SAT = 3.49 (0.82); ENG = 2.87 (0.93); PRIV = 3.71 (0.98); TR = 2.87 (0.82). Exact p values: AP–SAT $p < .001$; AP–ENG $p < .001$; AP–PRIV $p = .311$; AP–TR $p = .001$; SAT–ENG $p < .001$; SAT–PRIV $p = .823$; SAT–TR $p < .001$; ENG–PRIV $p = .065$; ENG–TR $p < .001$; PRIV–TR $p = .131$.

*** $p < .001$, ** $p < .01$, * $p < .05$ (two-tailed).

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As shown in Table 2, AI Personalization (AP) was positively and significantly correlated with Trust (TR), $r = .292$, $p = .001$, supporting H1 at the bivariate level, and with Satisfaction ($r = .713$, $p < .001$) and Engagement ($r = .557$, $p < .001$), supporting H2 and H3. Notably, Privacy Concerns (PRIV) exhibited a weak, non-significant negative correlation with Trust ($r = -.133$, $p = .131$).

This suggests a privacy paradox within this demographic: while users may express concern about data use, this concern does not significantly diminish their trust in platforms that provide personalized utility—consistent with the theoretical reconciliation proposed in §2.4, wherein narrow privacy concerns do not necessarily erode diffuse platform trust.

Hypothesis Testing: Multiple Regression Analysis

A hierarchical regression approach was used to determine the predictive influence of the study variables on Trust.

Step 1: Direct Effects Model

The results of the direct-effects model are presented in Table 3.1. As shown in Table 3.1, AI Personalization significantly predicted Trust, whereas Privacy Concerns showed only a marginal effect.

The initial model tested the direct impact of AI Personalization and Privacy Concerns on Trust. The model was statistically significant, $F(2, 127) = 7.90$, $p < .001$, explaining 11.1% of the variance ($R^2 = .111$, Adjusted $R^2 = .097$). AI Personalization was a significant positive predictor ($\beta = .31$, $p < .001$), supporting H1.

Privacy Concerns had a negative but only marginally significant effect ($\beta = -.16$, $p = .058$), providing weak, inconclusive support for H8 at this stage of the analysis.

Table 3.1 Hierarchical Regression Predicting Trust — Step 1: Direct-Effects Model

Predictor	B	SE B	β	t	p
Intercept	2.36	0.37	—	6.41	< .001
AP	0.28	0.08	.31	3.64	< .001
PRIV	−0.13	0.07	−.16	−1.91	.058

Note. N = 130. DV = Trust. $R^2 = .111$, Adjusted $R^2 = .097$, $F(2, 127) = 7.90$, $p < .001$. AP = AI Personalization; PRIV = Privacy Concerns. β = standardized coefficient. The intercept row has no standardized coefficient by definition.

Step 2: Extended Experiential Model

To examine whether Satisfaction and Engagement account for the relationship between AI Personalization and Trust, a second hierarchical step added these two variables to the model. The model was significant, $F(4, 125) = 16.10$, $p < .001$, $R^2 = .340$, Adjusted $R^2 = .319$—a significant increase of $\Delta R^2 = .229$ over the Step 1 model ($R^2 = .111$), F-change $(2, 125) = 21.73$, $p < .001$.

Table 3.2 presents the hierarchical regression results after adding Satisfaction and Engagement to the model. As shown in Table 3.2, the explanatory power of the model increased substantially, indicating the importance of experiential variables in explaining consumer trust.

Table 3.2 Hierarchical Regression Predicting Trust — Step 2: Extended Experiential Model

Predictor	B	SE B	β	t	p
Intercept	1.34	0.36	—	3.75	< .001
AP	−0.18	0.10	−.19	−1.78	.078
SAT	0.37	0.11	.38	3.36	.001
ENG	0.35	0.09	.39	4.05	< .001

Predictor	B	SE B	β	t	p
PRIV	−0.04	0.06	−.04	−0.59	.554

Note. N = 130. DV = Trust. $R^2 = .340$, Adjusted $R^2 = .319$, $F(4, 125) = 16.10$, $p < .001$. ΔR^2 (vs. Step 1) = .229, F-change(2, 125) = 21.73, $p < .001$.

When Satisfaction (SAT) and Engagement (ENG) were added to the model, explained variance increased significantly to 34.0% ($R^2 = .340$, $p < .001$). Satisfaction ($\beta = .38$, $p = .001$) and Engagement ($\beta = .39$, $p < .001$) were the strongest predictors of Trust, supporting H4 and H5. The direct effect of AI Personalization became non-significant, and its sign reversed ($B = −0.18$, $\beta = −.19$, $p = .078$), consistent with its influence operating through, rather than independently of, user experience. A negative point estimate for a residual direct path after entry of highly correlated mediators (AP–SAT $r = .71$; AP–ENG $r = .56$) is a known statistical pattern in mediation analysis and does not itself undermine the mediation interpretation, since the relevant test is the non-significance of the coefficient, not its sign; this is addressed further in §5.4.

Mediation Analysis

To test H6 and H7, a percentile bootstrap mediation analysis (5,000 resamples) was conducted using the product-of-coefficients method (Hayes 2022), estimating the indirect effect of AI Personalization on Trust through each of the two parallel mediators (Satisfaction, Engagement), net of Privacy Concerns. Each a-path (AP → mediator) was estimated as a simple regression of the mediator on AP; each b-path (mediator → TR) was taken from the Step 2 model in Table 3.2, which holds the other mediator and Privacy Concerns constant. Confidence intervals are 95% percentile bootstrap intervals; an indirect effect is considered statistically supported when its interval excludes zero.

Table 4. Bootstrap Mediation Analysis: Indirect Effects of AI Personalization on Trust Through Satisfaction and Engagement

Path	a	b	Indirect (a×b)	SE	95% CI	p	Result
AP → SAT → TR	0.66	0.37	0.25	0.12	[−0.01, 0.43]	.064	Marginal (H6)
AP → ENG → TR	0.58	0.35	0.20	0.06	[0.10, 0.33]	< .001	Supported (H7)
Total indirect effect	—	—	0.45	0.10	[0.23, 0.63]	< .001	Supported
Direct effect (c′)	—	—	−0.18	0.14	[−0.40, 0.12]	.281	Not significant

Note. N = 130. Unstandardized coefficients; percentile bootstrap, 5,000 resamples, controlling for Privacy Concerns. a = AP → mediator path; b = mediator → Trust path (from the Step 2 model). Direct effect c′ is the residual AP → Trust path once both mediators are in the model; its point estimate and standard error differ slightly from the Step 2 OLS estimate in Table 3.2 ($B = −0.18$, $SE = 0.10$, $p = .078$) because it is re-estimated here via bootstrap resampling rather than the OLS asymptotic formula — both tests agree that the direct effect is non-significant. Bootstrap p values are computed as 2 × min (proportion of resamples ≤ 0, proportion ≥ 0).

The total indirect effect of AI Personalization on Trust through Satisfaction and Engagement combined was statistically significant ($B = 0.45$, 95% CI [0.23, 0.63], $p < .001$), and the residual direct effect was non-significant in both the Step 2 regression ($p = .078$) and this bootstrap re-estimation ($p = .281$). Together these results support full mediation of the overall AI Personalization–Trust relationship: AI personalization does not build trust directly but by enhancing users' experiential states. Decomposed by pathway, however, the two mediators are not equally dependable. The Engagement-specific indirect effect was robust ($B = 0.20$, 95% CI [0.10, 0.33], $p < .001$), fully supporting H7. The Satisfaction-specific indirect effect was smaller in relative precision: its confidence interval extended to −0.01, just touching zero ($p = .064$), so H6 is treated as only marginally supported rather than conventionally confirmed at $\alpha = .05$. This pattern—in which Engagement is the more robust of the two mediators while Satisfaction's indirect effect is only marginal—is carried through consistently in the Discussion (§6.2) and Hypothesis Summary (Table 5) below.

Hypothesis Testing Summary

Table 5. Summary of Hypothesis Testing Results

Hyp.	Relationship	Key Statistic	Decision
H1	AP → TR (direct)	β = .31, $p < .001$ (Step 1); β = −.19, p = .078 (Step 2)	Supported at Step 1; effect fully mediated at Step 2
H2	AP → SAT	r = .713, $p < .001$	Supported
H3	AP → ENG	r = .557, $p < .001$	Supported
H4	SAT → TR	β = .38, p = .001 (Step 2)	Supported
H5	ENG → TR	β = .39, $p < .001$ (Step 2)	Supported
H6	SAT mediates AP → TR	Indirect = 0.25, 95% CI [−0.01, 0.43], p = .064	Marginally supported
H7	ENG mediates AP → TR	Indirect = 0.20, 95% CI [0.10, 0.33], $p < .001$	Supported
H8	PRIV → TR (negative)	r = −.133, p = .131; β = −.04, p = .554 (Step 2)	Not supported — privacy paradox observed

Note. AP = AI Personalization; SAT = Satisfaction; ENG = Engagement; PRIV = Privacy Concerns; TR = Trust. Statistics for H2 and H3 are zero-order Pearson correlations (Table 2); no separate single-predictor regression of SAT or ENG on AP was run, as the standardized simple-regression coefficient for a single predictor is numerically identical to its zero-order correlation.

SUMMARY OF FINDINGS

The empirical results show that AI Personalization predicts Trust only when considered in isolation (Step 1); once Satisfaction and Engagement enter the model (Step 2), this direct effect disappears and the total indirect effect through both mediators combined is significant, supporting full mediation of the overall relationship. Decomposed by pathway, Engagement emerges as the more dependable proximal driver of trust, while the Satisfaction-specific pathway is only marginally significant in this sample. Personalization therefore functions primarily as the technological antecedent that triggers these experiential states, which in turn shape platform trust. Privacy Concerns, contrary to the conventional trust-erosion assumption, showed no significant relationship with Trust at any stage of the analysis—evidence of a privacy paradox specific to this digital-native sample.

DISCUSSION

AI Personalization and Trust

Consistent with prior technology-adoption research, AI Personalization initially showed a significant positive effect on Trust in the direct regression model, suggesting users perceive personalized AI systems as more reliable and better aligned with their preferences. However, once Satisfaction and Engagement entered the model, this direct effect became non-significant. This pattern echoes Jeong et al.'s (2022) finding that personalized recommendation stimuli affect purchase behavior only through an intervening positive-emotion state, and Guo et al.'s (2022) demonstration that service stimuli operate through, rather than around, experiential mediators. The present study extends this pattern from purchase and service outcomes into the specific domain of AI-enabled consumer trust, indicating that personalization does not independently generate trust but must first translate into a satisfying, engaging experience.

Mediating Role of Satisfaction and Engagement

The mediation analysis supports full mediation of the overall AI Personalization–Trust relationship: the total indirect effect through Satisfaction and Engagement combined was significant, while the residual direct effect was not. This indicates that trust formation in AI-enabled platforms is primarily experience-driven rather than feature-driven: users do not trust AI because it is personalized, but because personalization enhances their overall experience of the platform. The two experiential mediators, however, did not contribute equally. Engagement produced a robust, precisely estimated indirect effect, whereas the Satisfaction-specific pathway was smaller and only marginally significant, with its confidence interval extending to just below zero. A plausible explanation is that Satisfaction and Engagement are themselves strongly correlated ($r = .619$, $p < .001$, Table 2) and both correlate substantially with AI Personalization ($r = .713$ and $r = .557$, respectively); once both are entered simultaneously as parallel mediators, Engagement may capture variance in the behavioral pathway to trust that overlaps with, and statistically outcompetes, the evaluative pathway captured by Satisfaction. Practically, this suggests that active behavioral engagement with personalized features—rather than post-hoc satisfaction judgments alone—is the more dependable lever through which personalization builds trust in this sample, though both experiential states plausibly matter within the broader S-O-R process.

Privacy Concerns and Trust: Reconciling a Contested Finding

Contrary to the conventional privacy–trust assumption, Privacy Concerns did not significantly predict Trust in the extended model. This finding sits in productive tension with McKee et al. (2023), who report that privacy–benefit trade-offs strongly shape Gen Z consumers' brand-avoidance intentions. We suggest the apparent conflict is a matter of construct specificity rather than contradiction: brand avoidance is a discrete behavioral reaction to a salient privacy trigger, whereas generalized platform trust is a slower-forming, more diffuse evaluation that experiential benefits (satisfaction, engagement) can offset even when residual privacy concern persists. This tension has since been formalized as a 'transformative privacy calculus,' in which consumers' broader emotional relationship with digital environments — not privacy concern in isolation — shapes how personalization benefits and privacy costs are weighed (Cloarec, Meyer-Waarden, and Munzel 2024), lending further support to treating generalized platform trust as distinct from situational privacy reactions. This distinction is itself a contribution: it suggests future privacy-paradox research should specify which outcome variable (behavioral avoidance vs. generalized trust) is being modeled, since the paradox may hold for one and not the other within the same population. The buffering role of trust is echoed in very recent work showing that brand trust significantly moderates the negative effect of privacy concerns on consumer well-being in AI-driven e-commerce, weakening — though not eliminating — the personalization–privacy paradox's psychological cost (Aydin 2026).

Theoretical and Managerial Implications

Theoretical Contributions

This study makes four contributions to the literature on AI and consumer behavior in e-commerce. First, it extends the S-O-R framework by conceptualizing AI-driven personalization as a technological stimulus that influences trust through experiential mechanisms, moving S-O-R e-commerce research (Jeong et al. 2022; Guo et al. 2022; Ric and Benazić 2022) from purchase-intention and loyalty outcomes into the domain of algorithmic trust formation specifically.

Second, the study advances trust theory by demonstrating the differential mediating roles of Satisfaction and Engagement—with Engagement emerging as the more robust of the two experiential mechanisms—contributing to the literature by identifying consumer experience, and behavioral engagement in particular, as the mechanism through which technological capability translates into relational outcomes, addressing the heterogeneity in AI-acceptance determinants documented by Kelly et al. (2023).

Third, the study provides empirical evidence on the privacy paradox using data from young Indian consumers—a population underrepresented relative to the Western and East Asian samples that dominate this literature (cf. McKee et al. 2023)—and offers a construct-specificity explanation (§6.3) for why privacy-paradox findings diverge across studies, a reconciliation that has not, to our knowledge, been explicitly proposed elsewhere.

Fourth, the study integrates TAM, Privacy Calculus Theory, and the S-O-R framework into a unified explanation of trust formation in AI-enabled commerce, combining technological, experiential, and privacy-related perspectives into a more comprehensive account than any single theory provides in isolation.

Managerial Implications

First, organizations should recognize that AI personalization alone is insufficient to build consumer trust; trust develops primarily through positive user experiences characterized by satisfaction and, especially, active engagement. Firms should therefore design AI systems that provide accurate recommendations and enhance overall customer experience.

Second, e-commerce platforms should invest in strategies that increase consumer engagement in particular—interactive recommendation systems, gamified or conversational touchpoints, and user-friendly interfaces that invite active use rather than passive receipt of recommendations—since these experiential factors, not algorithmic sophistication per se, transform technological capability into long-term trust and loyalty; satisfaction-oriented investments remain worthwhile but, on this evidence, may be the secondary lever.

Third, although privacy concerns showed limited direct impact on trust among digital-native consumers, organizations should not disregard privacy protection. Transparent data practices and clear communication about data use remain essential for maintaining credibility and reducing consumer resistance, particularly given that the same demographic shows strong privacy-driven avoidance behavior in other contexts (McKee et al. 2023).

Finally, managers should adopt a balanced approach combining personalization with responsible data governance, delivering meaningful value while ensuring transparency and ethical data use to strengthen trust and sustain customer relationships in AI-driven digital marketplaces.

CONCLUSION

This study set out to resolve two persistent uncertainties in AI-driven e-commerce research: whether personalization builds trust directly or through an experiential process, and whether privacy concerns meaningfully constrain that trust among digital-native consumers. The results answer both questions with a single, internally consistent model. AI Personalization's effect on Trust is fully mediated, in aggregate, by Satisfaction and Engagement—the direct path, significant in isolation ($R^2 = .111$), disappears once the experiential mediators are introduced ($R^2 = .340$)—demonstrating that trust in AI-enabled platforms is experience-driven rather than feature-driven. Within that aggregate mediation, Engagement is the more dependable specific pathway, while Satisfaction's contribution, though positive, is only marginal at conventional significance thresholds in this sample. Simultaneously, Privacy Concerns showed no significant relationship with Trust, evidencing a privacy paradox among Indian digital natives that we reconcile against conflicting Gen Z evidence (McKee et al. 2023) by distinguishing generalized trust from discrete avoidance behavior.

The novelty of this contribution is threefold: (1) it supplies rare bootstrapped-mediation evidence for the S-O-R "experiential bridge" specifically in the AI-personalization–trust relationship, rather than in purchase-intention or loyalty outcomes, and shows that the bridge's two component planks are not equally load-bearing; (2) it offers a construct-specificity explanation for why privacy-paradox findings diverge across the literature; and (3) it grounds both findings in an understudied population—young Indian e-commerce consumers—extending the geographic and demographic reach of this research stream. In sum, AI systems build trust not merely by being intelligent or personalized, but by creating meaningful, engaging user experiences; personalization is the antecedent, experience (engagement in particular) is the mechanism, and trust is the outcome.

Limitations and Future Research

This study has several limitations. First, the sample size (N = 130), while adequate for the regression and bootstrapped mediation analyzes reported here, is modest relative to current minimum-sample-size guidance for SEM-based mediation testing (Hair et al. 2022) and may limit generalizability; the marginal (rather than clearly significant) Satisfaction-specific indirect effect reported in §5.4 is consistent with a sample that is adequately, but not generously, powered to detect two simultaneous parallel mediators of moderate size. Future studies should replicate these findings with larger, more diverse samples to establish whether the Satisfaction pathway strengthens with additional power or remains genuinely smaller than the Engagement pathway. Second, the use of self-reported, cross-sectional data restricts causal inference and leaves the model susceptible to common method bias; longitudinal or experimental designs (cf. Jeong et al. 2022, who used an actual online purchase environment rather than survey self-report) would strengthen causal claims. Third, the study examined a limited construct set (AI Personalization, Satisfaction, Engagement, Privacy Concerns, and Trust); other relevant factors such as perceived usefulness, algorithmic transparency, and algorithmic fairness were not examined and represent promising extensions. Finally, the analysis was confined to a specific national and platform context, which may shape perceptions of AI and trust in ways that limit transferability to other markets. Future research may address these limitations through longitudinal designs, larger and more diverse samples, and the incorporation of transparency and fairness constructs alongside the experiential mediators tested here.

Declaration

Generative AI tools such as ChatGPT, Gemini, and Claude were used solely for language editing and manuscript clarity. The author reviewed and edited all content carefully and takes full responsibility for the accuracy, originality, and integrity of the work. No AI tools were used to generate research data, perform analysis, or produce scientific conclusions.

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CRediT: **Christina J B:** conception and design of the study, data collection, data analysis and interpretation, drafting of the manuscript; **Dr Sandhya K:** Supervision, Formal analysis and Writing – Final draft of the manuscript.

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