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AI-Driven Personalization and Data-Centric Marketing in Indian FinTech: Empirical Evidence on Customer Satisfaction, Trust, and Engagement

Rahul Kumar
MBA Student, Faculty of Management Studies, CMS Business School, JAIN (Deemed-to-be University)

Dr. Govindaraj M
Associate Professor, Faculty of Management Studies, CMS Business School, JAIN (Deemed-to-be University)

Abstract

The rapid proliferation of Financial Technology (FinTech) has fundamentally transformed customer engagement paradigms in the Indian financial services sector. This study empirically investigates the influence of Artificial Intelligence (AI)-driven personalization and automation tools on customer satisfaction, trust, and engagement among Indian FinTech users. Grounded in the Technology Acceptance Model (TAM), UTAUT2, Privacy Calculus Theory, and Information Systems Trust Theory, the research adopts a quantitative cross-sectional design. Primary data were collected from 200 FinTech users across India using a structured Likert-scale questionnaire spanning eight constructs. Statistical analyses comprising one-sample t-tests, Pearson correlation analysis, and one-way ANOVA were executed using SPSS. Key findings reveal that AI personalization exerts the strongest positive influence on customer satisfaction ($r = 0.706$, $p < 0.01$) and trust ($r = 0.671$, $p < 0.01$). Automation exposure significantly correlates with engagement ($r = 0.438$, $p < 0.01$). Transparency positively moderates trust ($r = 0.478$, $p < 0.01$), while privacy risk demonstrates only a weak negative effect on trust ($r = -0.152$, $p < 0.05$) without influencing satisfaction. Digital literacy exhibits no significant moderating effect ($r = -0.064$, $p > 0.05$), indicating that contemporary FinTech interfaces have democratized AI benefits across literacy strata. The study validates three of five hypotheses and contributes novel context-specific evidence to the global FinTech personalization literature, offering actionable implications for practitioners and policymakers.

Keywords: FinTech, AI personalization, data-driven marketing, customer experience, automation, trust, privacy risk, digital literacy

INTRODUCTION

The global FinTech industry has undergone an unprecedented transformation over the past decade, propelled by digital disruption, evolving consumer expectations, and maturing regulatory ecosystems. The sector is projected to expand from USD 201.3 billion in 2023 to USD 514.9 billion by 2028, registering a compound annual growth rate of approximately 20.7% (Statista, 2024; KPMG, 2024). This explosive trajectory is not merely a function of technological advancement; it reflects a fundamental restructuring of how financial services are designed, delivered, and experienced (Carè et al., 2025; Verhoef et al., 2009).

India occupies a singular position within this global narrative. With over 12.20 billion Unified Payments Interface (UPI) transactions valued at approximately INR 18.41 lakh crore recorded in January 2024 alone, the country exemplifies how digital financial innovation can reshape macroeconomic participation at scale. The convergence of high mobile penetration, a young demographic dividend, and progressive regulatory initiatives, most notably the RBI's FinTech Repository and Account Aggregator Framework has catalyzed an environment where AI-powered personalization and automated marketing can operate at unprecedented granularity (Nanda & Yunus, 2024; Demir et al., 2020).

Personalization, broadly defined as the tailoring of products, services, and communications to individual preferences using data analytics and machine learning, has emerged as a primary competitive differentiator in FinTech (Peppers & Rogers, 2016; Amnas et al., 2024). AI-driven recommendation engines, behavioral targeting algorithms, and automated messaging platforms enable FinTech firms to deliver contextually relevant financial guidance from investment suggestions to credit alertst hat was hitherto unachievable through traditional segmentation methods. The Technology Acceptance Model (TAM) proposed by Davis (1989) and its successors, including UTAUT2 (Venkatesh et al., 2012), provide robust theoretical grounding for understanding how AI personalization enhances perceived usefulness and ease of use, thereby driving adoption and sustained engagement.

However, the deployment of AI on a scale introduces a complex set of tensions. Growing consumer awareness of data collection practices has heightened privacy risk perceptions (Naz et al., 2024; Dinev & Hart, 2006). The 'black box' nature of many machine learning algorithms raises questions of algorithmic transparency and erodes institutional trust (Kim & Park, 2022; McKnight et al., 2002). Simultaneously, debates around digital literacy as a moderating variable in AI adoption have intensified, particularly in the Indian context where educational attainment and digital access remain heterogeneous (Ha et al., 2025; Feghali et al., 2024).

Despite substantial scholarly attention to FinTech adoption in emerging markets, a critical empirical gap persists. Most extant studies focus on broad adoption determinants without isolating the specific mechanisms through which AI personalization and automation shape customer experience outcomes satisfaction, trust, and engagement in the Indian FinTech ecosystem. Furthermore, the moderating roles of privacy risk, algorithmic transparency, and digital literacy on these pathways remain insufficiently tested. This study addresses these gaps through a rigorous quantitative investigation of 200 Indian FinTech users, thereby contributing contextually situated empirical evidence to the global literature on AI-driven customer experience management (Kodongo, 2024; Beck, 2020; Adhikari et al., 2024; Ravi et al., 2024; Datta, 2024).

PROBLEM IDENTIFICATION

The central research problem emerges from a tripartite gap at the intersection of the empirical, conceptual, and contextual literature domains. Empirically, while FinTech adoption research has proliferated, systematic studies examining whether AI personalization genuinely translates into measurable satisfaction and trust gains in the Indian market remain sparse. Conceptually, the moderating architecture of privacy risk and transparency within AI-driven service encounters has not been comprehensively modeled; most studies treat these constructs as antecedents rather than moderating or mediating variables. Contextually, the Indian FinTech landscape characterized by diverse service modalities including Digital Banking, Digital Lending, and Personal Finance Management/Investment presents a unique comparative opportunity that existing cross-country studies have inadequately captured.

This research therefore poses the following central question: To what extent do AI-driven personalization and automation tools in FinTech positively influence customer satisfaction, trust, and engagement, and how do privacy risk perception, transparency, and digital literacy moderate these outcomes among Indian FinTech users? Addressing this question yields implications for FinTech product managers, data governance practitioners, regulators, and academic scholars advancing the frontier of AI-driven customer experience research.

LITERATURE REVIEW

Personalization in financial services encompasses the algorithmic tailoring of products, services, communications, and digital touchpoints to individual user profiles derived from behavioral, transactional, and contextual data. The TAM framework (Davis, 1989) establishes that perceived usefulness the degree to which users believe technology enhances their performance is the primary cognitive antecedent of adoption. In the FinTech context, AI personalization operationalizes perceived usefulness by delivering financial recommendations that are accurate, relevant, and timely (Amnas et al., 2024). Venkatesh et al.'s (2012) UTAUT2 model extends this foundation by incorporating hedonic motivation the pleasure derived from using a system as an additional adoption driver; AI personalization contributes to hedonic motivation through the affective dimension of receiving advice that feels individually understood.

Empirical evidence supports a robust positive relationship between personalization quality and customer satisfaction. Verhoef et al. (2009) establish that personalization is among the most potent determinants of customer experience creation in retail services, a finding that translates directly to digital financial services. Adhikari et al. (2024) demonstrate that trust, performance expectancy, and effort expectancy conjointly drive FinTech adoption, with personalization quality as a primary driver of performance expectancy. Carè et al. (2025) note that AI-powered platforms have enabled financial access for millions globally, positioning personalization as both a commercial strategy and an inclusion mechanism.

Automated communication tools encompassing push notifications, in-app alerts, robo-advisors, and conversational AI chatbots constitute a second dimension of AI deployment in FinTech. These tools operate on a scale, maintaining continuous customer contact without proportional increases in human resource costs. Ravi et al. (2024) identify automation capabilities as foundational to FinTech firms' ability to serve underbanked and underserved populations, suggesting that automation's impact extends beyond engagement to financial inclusion. The relationship between automation exposure and customer engagement is theoretically mediated by service utility: automation that delivers contextually relevant information increases platform revisit frequency and breadth of service usage (Peppers & Rogers, 2016).

However, automation carries an intrinsic risk of message fatigue and perceived intrusiveness when frequency or relevance calibration is poor. This study uniquely examines the empirical correlation between automation exposure quality and behavioral engagement outcomes, filling a gap in the literature regarding automation's net effect across diverse Indian FinTech service categories.

The Privacy Calculus Theory (Dinev & Hart, 2006) posits that individuals engage in a cost-benefit evaluation when deciding to share personal data, weighing perceived privacy risks against expected benefits. In AI-powered FinTech environments, this calculus is particularly complex: users must trust that behavioral data collected to enable personalization will not be misappropriated, sold, or used for purposes beyond the disclosed scope. Naz et al. (2024), in a systematic analysis of 250 FinTech studies in the MENA region, identify privacy concerns and cybercrime risks as primary structural barriers to sustained FinTech adoption. Similarly, Nanda and Yunus (2024) emphasize that regulatory clarity and cybersecurity assurance are preconditions for FinTech-driven financial inclusion.

Transparency in AI operations, the extent to which users understand how algorithmic recommendations are generated and what data informs them has emerged as a trust-building mechanism within Information Systems Trust Theory (McKnight et al., 2002). Kim and Park (2022) demonstrate that explainable AI (XAI) features plain-language explanations of recommendation logic, 'why am I seeing this?' disclosures, and data usage dashboards significantly increase consumer trust in financial recommendation systems. Importantly, transparency also functions as a privacy risk reducer: consumers who understand how their data is used perceive lower risks of misuse (McKnight et al., 2002). This 'double dividend' positions transparency as a dual-benefit strategic investment for FinTech firms rather than merely a compliance obligation.

Digital literacy defined as the ability to find, evaluate, and use digital information effectively, including understanding how AI-driven features function—has been theorized as a moderator of AI adoption and personalization efficacy (Ha et al., 2025). Higher digital literacy enables users to interpret, critically evaluate, and act upon AI recommendations more effectively, theoretically amplifying personalization's impact on satisfaction. Demir et al. (2020) find that lower digital literacy among underserved communities constitutes a barrier to FinTech adoption, supporting the moderation hypothesis.

However, emerging evidence suggests this moderation effect may be diminishing as AI interface design advances. Improved natural language processing, voice-first interfaces, simplified UX design patterns, and regional language support have collectively lowered the cognitive barrier to benefiting from personalization features. This study empirically tests whether digital literacy remains a significant moderator in the contemporary Indian FinTech context, contributing to an ongoing debate in the literature regarding whether 'design determines adoption' is superseding 'access determines adoption' (Ha et al., 2025; Feghali et al., 2024).

RESEARCH GAP

Despite a growing body of literature on FinTech adoption, four specific gaps motivate this study. First, limited empirical work isolates the direct pathway from AI personalization quality to customer satisfaction and trust in the Indian FinTech market, where market structure, regulatory environment, and user demographics differ significantly from Western or East Asian contexts studied in the extant literature. Second, the moderating roles of privacy risk perception and algorithmic transparency within the AI personalization–trust–satisfaction triad have not been jointly examined in a single empirical study on Indian FinTech users. Third, the question of whether digital literacy retains its theorized moderating function in increasingly intuitive AI-powered FinTech environments has not been empirically resolved for the Indian market. Fourth, comparative analysis of AI personalization effectiveness across distinct FinTech service categories Digital Banking, Digital Lending, and PFM/Investment is notably absent from existing literature, limiting the granularity of practitioner recommendations. This study addresses all four gaps through an integrated quantitative design.

RESEARCH METHODOLOGY

This study adopts a positive, quantitative research paradigm employing a cross-sectional survey design. The research philosophy aligns with deductive theory-testing, as hypotheses were derived from established theoretical frameworks including TAM, UTAUT2, Privacy Calculus Theory, and Information Systems Trust Theory prior to data collection.

The target population comprised active FinTech users in India individuals who had used at least one FinTech platform in the preceding 12 months. A non-probability purposive sampling technique was employed, supplemented by snowball sampling through professional and academic networks. A final sample of N = 200 respondents was achieved, exceeding the minimum threshold recommended for Pearson correlation and ANOVA analyses (Cohen, 1988). All respondents were adults (18+) and primary users of Digital Banking, Digital Lending, or PFM/Investment platforms.

The research instrument comprised a structured questionnaire divided into two sections. Section A collected six demographic variables: age group, gender, education level, occupation, years of FinTech experience, and primary FinTech service category. Section B contained 20 Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree) measuring eight constructs: AI Personalization (Q1–Q4), Automation Exposure (Q5–Q7), Customer Satisfaction (Q8–Q10), Customer Engagement (Q11–Q12), Privacy Risk (Q13–Q14), Transparency (Q15–Q16), Trust (Q17–Q18), and Digital Literacy (Q19–Q20). Item content was adapted from validated scales in the FinTech adoption and customer experience literature.

Internal consistency of each construct was assessed via Cronbach's alpha coefficients. Composite construct means and standard deviations were computed for descriptive analysis. One-sample t-tests compared each construct mean against the neutral midpoint of 3.0. Pearson correlation coefficients were computed for all construct pairs to test the directional hypotheses. One-way ANOVA assessed whether customer experience outcomes varied significantly across demographic sub-groups. All analyses were conducted using IBM SPSS Statistics 26.0, with the significance threshold set at $p < 0.05$.

The five research hypotheses are as follows:

H1: Higher AI personalization exposure leads to greater customer satisfaction (positive direction).

H2: Greater automation tool exposure positively influences customer engagement (positive direction).

H3: Privacy risk perception negatively moderates the AI personalization–satisfaction relationship (negative direction).

H4: Higher perceived transparency in AI operations positively influences consumer trust (positive direction).

H5: Digital literacy positively moderates the perceived effectiveness of AI personalization (positive direction).

DATA ANALYSIS

Profile of Respondents

The respondent profile reveals a technologically engaged, educationally advanced sample well-positioned to evaluate AI personalization quality. Young professionals aged 25–35 constitute the plurality (42.5%), consistent with India's demographic dividend and the concentration of FinTech heavy-users in working-age cohorts. The near-gender parity (52% male, 47% female) is noteworthy in the Indian context, historically characterized by gender-skewed financial service access, and enhances the generalizability of findings across gender demographics. The educational profile 96.5% holding undergraduate or higher qualifications—reflects the urban, technology-oriented FinTech user base and suggests high baseline digital literacy. Private sector employees form the occupational plurality (49.5%), reflect FinTech's value proposition for time-constrained professionals with discretionary income. Crucially, 71.5% of respondents have used FinTech platforms for two or more years, providing a well-experienced base capable of meaningful evaluation of AI feature quality across platform iterations. Digital Banking dominates service usage (44.5%), consistent with the dominance of payment apps in India's FinTech ecosystem.

Reliability Analysis

All eight constructs demonstrate Cronbach's alpha coefficients within the acceptable range ($\alpha > 0.70$), confirming adequate internal consistency for subsequent inferential analyses. AI Personalization achieves the highest composite mean (M = 3.651, SD = 0.750), establishing it as the most positively perceived construct in the study. This result validates the increasing sophistication of recommendation engine algorithms deployed by leading Indian FinTech platforms. Privacy Risk records the lowest mean (M = 2.583, SD = 0.928), reversed from its theoretical direction, indicating that the sample does not exhibit pronounced privacy anxiety—a positive signal for FinTech adoption sustainability and a finding that warrants contextual explanation considering India's evolving data governance landscape. Trust records the lowest among customer experience constructs (M = 3.385, SD = 0.745), reflecting the ambivalence observed in frequency distributions where a substantial neutral cluster (46–47%) coexists with positive agreement proportions, suggesting that trust remains a work in progress despite satisfactory AI performance perceptions.

Pearson Correlation Analysis

The Pearson correlation matrix reveals a theoretically coherent and empirically robust network of relationships. AI Personalization demonstrates the strongest bivariate association with Customer Satisfaction ($r = 0.706$, $p < 0.01$), establishing personalization quality as the preeminent driver of positive customer experience in this sample a finding that aligns with and strengthens Verhoef et al. (2009) and Amnas et al. (2024). The strong AI Personalization–Trust correlation ($r = 0.671$, $p < 0.01$) reveals that personalization quality builds brand trust beyond mere transactional satisfaction, extending the theoretical reach of TAM's perceived usefulness construct into the trust domain. Automation Exposure correlates meaningfully with both Satisfaction ($r = 0.598$, $p < 0.01$) and Engagement ($r = 0.438$, $p < 0.01$), confirming H2 and partially validating automation as a value-creating mechanism when calibrated for relevance and frequency. Transparency positively correlates with Trust ($r = 0.478$, $p < 0.01$) while exhibiting a negative correlation with Privacy Risk ($r = -0.210$, $p < 0.01$), establishing transparency as a dual-benefit strategic construct that simultaneously amplifies trust and attenuates privacy anxiety finding consistent with Kim and Park (2022). Privacy Risk's relationship with Satisfaction is non-significant ($r = 0.029$, $p = 0.684$), indicating that privacy concerns do not directly suppress satisfaction within this sample's utility calculus, though its weak negative association with Trust ($r = -0.152$, $p < 0.05$) confirms a partial effect consistent with H3. The non-significant Digital Literacy–AI Personalization correlation ($r = -0.064$, $p = 0.367$) leads to the rejection of H5, suggesting that contemporary FinTech interfaces have successfully democratized personalization benefits across literacy strata.

One-Sample t-Test Results

One-sample t-tests confirm that all six customer experience constructs demonstrate means significantly above the neutral midpoint of 3.0 (all $p < 0.001$). AI Personalization records the highest t-statistic ($t = 12.277$, $df = 199$), reflecting the strongest and most consistent positive consensus in the sample. The narrow 95% confidence interval [3.547, 3.756] confirms the precision of this estimate. Trust, while statistically significant ($t = 7.311$, $p < 0.001$), displays the widest confidence interval [3.281, 3.489] and the lowest t-value among constructs, consistent with the large neutral cluster observed in frequency distributions. These results confirm that all major constructs in the study are significantly positive in their aggregate orientation, supporting the broader argument that Indian FinTech's AI-driven service delivery is creating net-positive customer experiences relative to neutrality. Critically, no construct falls below the neutral midpoint, indicating an absence of widespread negative sentiment toward any dimension of AI-powered FinTech services in this sample.

One-Way ANOVA Analysis

The one-way ANOVA reveals a theoretically significant pattern: Customer Engagement varies meaningfully across FinTech service types ($F = 3.203$, $p = 0.043$), while Satisfaction and Trust are invariant across age groups, education levels, and FinTech experience duration. The engagement variation finding is substantively important: Digital Banking and PFM/Investment users report higher engagement means than Digital Lending users ($M = 3.237$), suggesting that AI personalization translates more effectively into behavioral engagement in daily-use, habitual service contexts than in episodic, need-based lending contexts. This context-dependency represents a nuanced extension to TAM that prior literature has not fully articulated for the FinTech domain. The invariance of Satisfaction across age groups, education levels, and experience duration constitutes a particularly strong finding, indicating that AI-driven personalization delivers comparable satisfaction quality regardless of user demographic profile—a result with significant implications for inclusive FinTech design strategy.

Hypothesis Testing Summary

DISCUSSION

This study's findings collectively reinforce and extend the extant literature on AI-driven customer experience in FinTech while contributing novel contextual evidence from the Indian market. The confirmation of H1 ($r = 0.706$) represents the most emphatic finding, establishing AI personalization quality as the dominant predictor of customer satisfaction—a result that aligns with Verhoef et al. (2009) and substantially strengthens Amnas et al. (2024) who identified perceived service quality as a foundational adoption determinant. The magnitude of this correlation ($r = 0.706$) is notably higher than the $r = 0.55–0.60$ range typically reported in comparable Western-market studies, suggesting that Indian FinTech users may place particularly high weight on personalization quality given the historically impersonal nature of traditional Indian banking services. This aligns with Carè et al.'s (2025) argument that personalization's impact is amplified in markets where formal financial service access was previously constrained.

The confirmation of H2 ($r = 0.438$, Automation–Engagement) is directionally consistent with Ravi et al. (2024) but reveals automation's more modest engagement effect relative to personalization. This divergence is theoretically meaningful: while automation enhances platform utility through timely information delivery, it lacks the affective resonance of individualized personalization. The large neutral cluster (38–40%) in automation items suggests that FinTech automation has achieved baseline adequacy without yet delivering differentiated value, indicating an opportunity space for next-generation context-aware automation systems.

The partial support for H3 is among the study's most theoretically interesting findings. Privacy Risk fails to moderate the AI personalization–satisfaction relationship ($r = 0.029$, n.s.), suggesting that within the Privacy Calculus (Dinev & Hart, 2006), satisfaction benefits are robust to privacy anxieties in this sample. However, the weak but significant negative Privacy Risk–Trust relationship ($r = -0.152$, $p < 0.05$) confirms that privacy concerns do erode institutional trust, albeit modestly. This aligns with Naz et al. (2024) but contradicts studies suggesting stronger privacy–satisfaction linkages in Western contexts, indicating meaningful cross-cultural variation in privacy calculus dynamics. The low overall Privacy Risk mean ($M = 2.583$) may reflect effective regulatory signaling through India's PDPB framework and established UPI trust infrastructure.

The confirmation of H4 ($r = 0.478$, Transparency–Trust) is consistent with Kim and Park (2022) and McKnight et al. (2002), positioning transparency as a critical trust-building lever. The 'double dividend' of transparency simultaneously increasing trust while reducing privacy concerns ($r = -0.210$) extends Kim and Park's (2022) XAI-trust findings by empirically demonstrating the privacy-attenuating dimension of transparency in the FinTech context. This finding carries significant strategic implications: investments in Explainable AI features, data usage dashboards, and plain-language recommendation explanations yield compounding returns across both trust and privacy dimensions.

The rejection of H5 ($r = -0.064$, n.s.) is arguably the most significant finding for FinTech inclusion strategy. Contrary to

Ha et al. (2025) and Demir et al. (2020), this study finds that digital literacy does not moderate AI personalization efficacy in contemporary Indian FinTech. This finding is consistent with the 'design determines adoption' paradigm shift argued by Beck (2020): advances in NLP, voice-first interfaces, regional language support, and simplified UX design have collectively reduced the literacy barrier to personalization benefit. FinTech firms can thus extend AI personalization to users across the digital literacy spectrum without sacrificing outcome quality, a finding with direct relevance to India's financial inclusion agenda.

CONCLUSION

This study contributes empirically grounded, context-specific evidence on the mechanisms through which AI personalization and automation tools shape customer experiences in the Indian FinTech sector. The principal conclusion is that AI personalization quality is the most powerful determinant of customer satisfaction and trust, surpassing automation, transparency, and all other constructs examined. Three of five hypotheses are confirmed, establishing directional empirical support for the theorized relationships between AI-driven personalization, automation, transparency, and customer experience outcomes.

The study's theoretical contributions are threefold. First, it extends TAM and UTAUT2 by empirically mapping the AI personalization–satisfaction–trust pathway within the Indian FinTech context, providing a more granular operationalization of perceived usefulness. Second, it establishes transparency as a 'double dividend' construct that simultaneously builds trust and reduces privacy anxiety, advancing Privacy Calculus Theory and Information Systems Trust Theory. Third, it provides the first empirical refutation of digital literacy moderation in the contemporary Indian FinTech context, supporting a paradigm shift toward design-driven AI inclusion.

For practitioners, the findings recommend three strategic priorities: investing in recommendation engine accuracy and timeliness as primary satisfaction drivers; deploying Explainable AI features and transparent data governance as trust-building mechanisms; and extending AI personalization strategies to users across digital literacy strata without discrimination. For policymakers, the study affirms the trust-enabling role of transparent regulatory communication and supports the RBI's ongoing initiatives around data protection and algorithmic accountability.

SCOPE FOR FURTHER RESEARCH

This study opens multiple avenues for future scholarly inquiry. First, a longitudinal panel design would enable researchers to track the evolution of AI personalization quality perceptions and their satisfaction outcomes over time, addressing the cross-sectional limitation of the current study and capturing learning effects as AI algorithms are continuously refined through user interaction data. Second, the service-type variation in engagement outcomes identified through ANOVA warrants deeper investigation: qualitative research within Digital Lending contexts could reveal why AI personalization generates lower behavioral engagement in episodic, need-based service interactions compared to habitual daily-use banking contexts. Third, Structural Equation Modeling (SEM) would enable simultaneous estimation of direct, indirect, and moderating pathways within a comprehensive measurement and structural model, providing effect size decomposition not possible with bivariate correlation analysis. Fourth, the Privacy Calculus dynamics observed in this study particularly the weak privacy satisfaction relationship merit cross-cultural validation across diverse regulatory environments, including GDPR-governed European markets and less-regulated Southeast Asian FinTech contexts, to assess the boundary conditions of this finding.

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Table 1
Profile of Respondents (N = 200)

Category	Sub-Category	Frequency	Percent (%)
Age Group	18–24	33	16.5
	25–35	85	42.5
	36–45	49	24.5
	46–55	25	12.5
	56+	8	4.0
Gender	Male	104	52.0
	Female	94	47.0
	Non-binary	2	1.0
Education Level	Undergraduate	79	39.5
	Postgraduate	94	47.0
	Doctoral	21	10.5
	Other	6	3.0
Occupation	Private Sector	99	49.5
	Public Sector	38	19.0
	Student	29	14.5
	Self-Employed	27	13.5
	Other	7	3.5
FinTech Experience	< 1 year	20	10.0
	1–2 years	37	18.5
	2–5 years	72	36.0
	5+ years	71	35.5
FinTech Service Type	Digital Banking	89	44.5
	Digital Lending	59	29.5
	PFM / Investment	52	26.0
Total		**200**	**100.0**

Note. Data collected via structured questionnaire survey, 2025–2026.

Table 2
Reliability Analysis and Descriptive Statistics by Construct

Construct	Items	Mean	Std Dev	Cronbach's α	Reliability
AI Personalization	Q1–Q4	3.651	0.750	0.821	Acceptable
Automation Exposure	Q5–Q7	3.447	0.703	0.784	Acceptable
Customer Satisfaction	Q8–Q10	3.463	0.658	0.796	Acceptable

Construct	Items	Mean	Std Dev	Cronbach's α	Reliability
Customer Engagement	Q11–Q12	3.447	0.772	0.751	Acceptable
Privacy Risk	Q13–Q14	2.583	0.928	0.812	Acceptable
Transparency	Q15–Q16	3.455	0.677	0.769	Acceptable
Trust	Q17–Q18	3.385	0.745	0.803	Acceptable
Digital Literacy	Q19–Q20	3.310	0.889	0.744	Acceptable

Note. Cronbach's α > 0.70 indicates acceptable reliability (Nunnally, 1978). Privacy Risk mean is presented as scored (higher score = more privacy concern).

Table 3

Pearson Correlation Matrix of Construct Pairs (N = 200)

Construct	AI Pers.	Auto Exp.	Satisf.	Engage.	Privacy	Transp.	Trust	Dig. Lit.
AI Pers.	1.000	0.626**	0.706**	0.582**	-0.055	0.507**	0.671**	-0.064
Auto Exp.	0.626**	1.000	0.598**	0.438**	-0.043	0.413**	0.465**	-0.031
Satisf.	0.706**	0.598**	1.000	0.445**	0.029	0.412**	0.581**	-0.012
Engage.	0.582**	0.438**	0.445**	1.000	-0.018	0.356**	0.398**	0.043
Privacy	-0.055	-0.043	0.029	-0.018	1.000	-0.210**	-0.152*	0.051
Transp.	0.507**	0.413**	0.412**	0.356**	-0.210**	1.000	0.478**	0.062
Trust	0.671**	0.465**	0.581**	0.398**	-0.152*	0.478**	1.000	0.028
Dig. Lit.	-0.064	-0.031	-0.012	0.043	0.051	0.062	0.028	1.000

Note. ** $p < 0.01$ (two-tailed); * $p < 0.05$ (two-tailed). Diagonal values represent construct correlations with themselves ($r = 1.000$).

Table 4

One-Sample t-Test Results (Test Value = 3.0, N = 200)

Construct	Mean	t-stat	df	Sig. (2-tail)	95% CI Lower	95% CI Upper
AI Personalization	3.651	12.277	199	0.000**	3.547	3.756
Automation Exposure	3.447	8.987	199	0.000**	3.349	3.545
Customer Satisfaction	3.463	9.957	199	0.000**	3.371	3.555
Customer Engagement	3.447	8.194	199	0.000**	3.340	3.555
Trust	3.385	7.311	199	0.000**	3.281	3.489
Transparency	3.455	9.511	199	0.000**	3.361	3.550

Note. ** $p < 0.01$ (two-tailed). Test value set at 3.0 (scale neutral midpoint). df = degrees of freedom. CI = Confidence Interval.

Table 5

One-Way ANOVA Results by Demographic Grouping Variable

Dependent Variable	Grouping Variable	F-statistic	p-value	Decision
Customer Satisfaction	Age Group	1.227	0.301	Not Significant
Trust	Education Level	0.511	0.675	Not Significant
Customer Engagement	FinTech Service Type	3.203	0.043*	Significant
Customer Satisfaction	FinTech Experience	1.739	0.160	Not Significant

Note. * Significant at $p < 0.05$. Post-hoc analysis for significant ANOVA: Digital Banking ($M = 3.522$) and PFM/Investment ($M = 3.558$) > Digital Lending ($M = 3.237$).

Table 6

Hypothesis Testing Summary

H	Hypothesis Statement	Key Statistic	Direction	Decision
H1	AI personalization → Customer Satisfaction	$r = 0.706$, $p < 0.01$	Strong Positive	Accepted
H2	Automation Exposure → Customer Engagement	$r = 0.438$, $p < 0.01$	Moderate Positive	Accepted
H3	Privacy Risk negatively moderates AI–Satisfaction	$r = 0.029$ (n.s.); r(Privacy–Trust) = −0.152*	Partial negative effect on Trust only	Partially Accepted
H4	Transparency → Consumer Trust	$r = 0.478$, $p < 0.01$	Moderate Positive	Accepted
H5	Digital Literacy moderates AI Personalization efficacy	$r = -0.064$ (n.s.)	No significant moderation	Rejected

Note. ** $p < 0.01$; * $p < 0.05$; n.s. = not significant.