Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-3 |March: 2026
Original Researcher Article

AI in Banking 2.0: Investigating Customer Experience, Trust, and Adoption Behavior in India.

Charmee Shah[1]*, Dr. Apeksha Champaneri[2]
[1] PhD Scholar, GLS University, Ahmedabad, Gujarat, India.
[2] Assistant Professor, GLS University, Ahmedabad, Gujarat, India.
Corresponding Author:
Charmee Shah
Email: Charmeesheth@gmail.com..

ABSTRACT
The rapid deployment of Artificial Intelligence technologies in Indian banking—including Chabot, fraud detection, robo-advisory, and biometric authentication—has exposed a persistent trust-adoption gap between institutional capability and customer willingness. This study develops and tests an integrated framework synthesizing the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate relationships among AI-driven banking features, customer experience (CX), trust, perceived risk, and adoption behavior. Data from 389 banking customers across metropolitan, semi-urban, and tier-2 Indian cities were analyzed using Partial Least Squares Structural Equation Modeling (SmartPLS 4.0). Seven hypotheses were tested via bootstrapping (5,000 subsamples), complemented by mediation decomposition and Importance-Performance Map Analysis (IPMA). AI features strongly enhance CX ($\beta = 0.68$, $p < 0.001$), which predicts adoption ($\beta = 0.54$, $p < 0.001$). Trust operates dually—as direct predictor ($\beta = 0.47$, $p < 0.001$) and moderator amplifying the CX–adoption relationship ($\beta = 0.18$, $p < 0.01$). Perceived risk independently suppresses adoption ($\beta = -0.21$, $p < 0.001$), confirming its distinctness from trust. The model explains 58.3% of adoption variance ($R^2 = 0.583$; $Q^2 = 0.412$). Serial mediation yields a total indirect effect of $\beta = 0.810$. IPMA identifies trust as the highest-priority intervention area. The study contributes to technology adoption theory by demonstrating TAM-UTAUT complementarity and provides actionable recommendations for banks, policymakers, and technology providers....

Keywords: Artificial Intelligence (AI), Digital Banking, Customer Experience, Customer Adoption.......

INTRODUCTION

Background

The global banking industry has transformed from branch-centric models to digitally mediated ecosystems, with AI emerging as the most consequential enabler (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018). In India, smartphone penetration exceeding 750 million users, UPI, the JAM trinity, and a $31 billion fintech ecosystem have created fertile conditions for AI integration (RBI, 2022; Gupta & Tham, 2019). Banks deploy eight AI categories: NLP chatbots, ML fraud detection, robo-advisory, predictive analytics, biometric authentication, AI credit scoring, RPA, and voice assistants (Gomber et al., 2018; Hasan et al., 2022; Mhlanga, 2020). Despite heavy investment—projected to exceed $4 billion by 2025—a significant proportion of customers remain reluctant to embrace AI services fully, creating a —trust-adoption gap‖ that undermines ROI and limits transformative potential (Kumar & Gupta, 2021; Belanche et al., 2019). This gap is particularly pronounced in India, where cultural factors such as collectivism, hierarchical trust orientation, and varying levels of digital literacy across urban-rural divides create adoption dynamics distinct from the Western and East Asian markets where most existing research originates (Sinha et al., 2021). Understanding the psychological and experiential mechanisms that bridge or widen this gap is essential for both academic theory and banking practice.

Problem Statement

The central problem is the incomplete understanding of how CX with AI banking translates into adoption, and the mechanisms—trust and risk—that moderate this translation. Existing research applies TAM or UTAUT in isolation without integrating AI-specific experiential quality (Marangunıç & Erciş, 2020; Pillai et al., 2020). Three gaps persist: (1) limited Indian evidence despite unique cultural and regulatory conditions distinct from Western markets (Sinha et al., 2021); (2) no framework integrating TAM's parsimony (perceived usefulness and ease of use as foundational beliefs) with UTAUT's breadth (social influence, facilitating conditions) while modeling trust as both a direct predictor and a moderator of the experience-adoption relationship (Kaur et al., 2021; Tamilmani et al., 2021); (3) perceived risk is routinely collapsed into trust measures rather than operationalized independently, obscuring the differential managerial interventions each requires—trust-building via transparency versus risk-reduction via guarantees and fail-safes (Pavlou, 2003; Featherman & Pavlou, 2003; Sharma et al., 2022).

AI Technologies in Indian Banking

Figure 2: AI Technology Ecosystem in Indian Banking

Indian banks deploy eight major AI technology categories, each with distinct customer touch points and trust implications. NLP chatbots (SBI's SIA handling 10,000+ daily queries, HDFC's EVA with 5 million+ interactions) reduce resolution time by 60–70% (Hasan et al., 2022; Huang & Rust, 2021). ML fraud detection achieves 95%+ accuracy with 50–60% fewer false positives than rule-based systems (Cao et al., 2021; Bao et al., 2022). Robo-advisory cuts advisory costs 70–80% but faces algorithmic aversion—users prefer human judgment even when algorithms outperform (Belanche et al., 2019; Jung et al., 2019). Predictive analytics boosts cross-selling effectiveness by 30–40% through behavioral pattern analysis (Davenport & Ronanki, 2018). Biometric authentication (fingerprint, facial recognition, voice print) provides multi-factor security while eliminating password fatigue (Mhlanga, 2020). AI credit scoring incorporates alternative data (mobile usage, digital footprint) to extend assessment to 30–40% of applicants rejected by traditional models (Jagtiani & Lemieux, 2019). RPA automates compliance, reconciliation, and reporting with 60–80% processing reduction (Lacity & Willcocks, 2018). Voice banking assistants enable hands-free access, particularly relevant for accessibility and convenience (Balakrishnan & Dwivedi, 2021). Each technology category introduces distinct trust and risk dynamics that aggregate into the overall adoption decision.

Research Questions

RQ1: To what extent do AI features enhance CX through TAM's PU/PEOU lens?

RQ2: How does CX influence adoption behavior?

RQ3: What is trust's direct and moderating role in CX–adoption?

RQ4: Does perceived risk independently suppress adoption beyond trust?

RQ5: Which construct should managers prioritize for intervention?

Research Objectives

To examine AI features' effect on Customer Experience (CX) grounded in TAM,

To assess Customer Experience (CX's) influence on adoption extending UTAUT,

To evaluate trust's dual role;

To determine perceived risk's independent suppressive effect;

To generate prioritized recommendations through IPMA.

Scope of the Study

Geographically: public, private, and digital/neo banks across metropolitan (Mumbai, Delhi, Bangalore), semi-urban (Ahmedabad, Pune, Jaipur), and tier-2 cities (Vadodara, Surat, Indore). Technologically: all eight AI categories. Temporally: October 2024–January 2025. Respondents had used at least one AI banking service within 12 months.

Significance

Theoretical: Validates TAM-UTAUT integration with trust as moderator—untested in AI banking.

Empirical: 389 respondents across India's diverse landscape, addressing the Geographical gap (Dwivedi et al., 2021).

Methodological: PLS-SEM with mediation decomposition and IPMA for prioritized action (Ringle & Sarstedt, 2016).

Managerial: IPMA identifies trust as highest-priority construct.

Policy: Informs RBI's AI governance framework for responsible deployment.

Literature Review

Technology Acceptance Model (TAM)

Davis (1989) posited that perceived usefulness (PU) and perceived ease of use (PEOU) determine adoption intention. PU captures the degree to which a person believes the system enhances performance, while PEOU reflects perceived effort required. Extensively validated across e-commerce (Gefen et al., 2003), mobile banking (Alalwan et al., 2017), and internet banking (Akturan & Tezcan, 2012), TAM explains approximately 40% of usage intention variance. However, it has been criticized for excluding social and contextual factors relevant to complex service environments (Bagozzi, 2007; Benbasat & Barki, 2007). For AI banking specifically, TAM omits experiential quality of AI interactions, algorithmic trust, and risk perceptions associated with delegating financial decisions to automated systems (Pillai et al., 2020). The model's individual-level cognitive focus also fails to capture the institutional and social dynamics that shape technology adoption in collectivist cultures like India.

UTAUT

Venkatesh et al. (2003) synthesized eight competing models into UTAUT, identifying four core determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions—explaining approximately 70% of usage intention variance, substantially more than TAM alone. UTAUT2 (Venkatesh et al., 2012) extended the framework to consumer contexts by adding hedonic motivation, price value, and habit. Despite its superior predictive power, UTAUT does not model trust as either a direct or moderating variable, treats risk implicitly through performance expectancy rather than as an independent construct, and does not differentiate between technology experience quality and cognitive evaluations of system attributes (Tamilmani et al., 2021). In Indian digital banking, Rana et al. (2017) and Kaur et al. (2021) applied UTAUT but without incorporating AI-specific constructs or testing trust as a moderator of the experience-to-adoption pathway.

Rationale for Integration

TAM provides foundational beliefs shaping AI feature evaluation; UTAUT contributes social and contextual dimensions. This study integrates both by: (a) using PU/PEOU as antecedents of AI Feature evaluation; (b) incorporating social influence and facilitating conditions as controls; (c) positioning CX as a TAM-derived mediator; (d) adding Trust (moderator + predictor) and Perceived Risk (suppressor). This responds to calls by Dwivedi et al. (2021), Tamilmani et al. (2021), and Sinha et al. (2021).

AI in Banking: Evidence

Brynjolfsson and McAfee (2017) established AI's superior productivity impact in financial services. Huang and Rust (2021) classified AI into mechanical, thinking, and feeling intelligence. Cao et al. (2021) documented deep learning fraud detection reducing false positives by 50–60%; Bao et al. (2022) showed 97%+ accuracy. Jung et al. (2019) found robo-advisory faces algorithmic aversion. Jagtiani and Lemieux (2019) demonstrated AI credit scoring extending assessment to 30–40% more applicants. Lacity and Willcocks (2018) reported RPA achieving 60–80% processing reduction.

Customer Experience

Lemon and Verhoef (2016) conceptualized CX as a journey-level construct. Klaus and Maklan (2013) identified four quality dimensions. Jain et al. (2023) demonstrated ML-driven personalization elevates CX. Marangunıç and Erciş (2020) found digital service experience quality predicts banking loyalty. Roy et al. (2017) established AI reliability carries disproportionate weight in smart service quality.

Trust in AI Banking

Gefen et al. (2003) established trust reduces risk and increases transactional willingness. McKnight et al. (2002) developed competence-benevolence-integrity dimensions. Rai (2020) argued explainability is a trust prerequisite. Glikson and Woolley (2020) proposed embedded AI trust develops through transparency and reliability. Lee and See (2004) showed both over-and under-trust impair outcomes. Kumar and Gupta (2021) found Indian data breaches have made trust a threshold condition.

Perceived Risk

Pavlou (2003) demonstrated risk and trust are conceptually distinct. Featherman and Pavlou (2003) identified six risk facets. Belanche et al. (2019) found performance and financial risk reduce robo-advisory adoption. Trust-building (transparency) and risk-reduction (guarantees, fail-safes) require separate interventions.

Literature Summary

Table 1: Key Literature

Authors	Focus	Key Findings	Gap Addressed
Davis (1989)	TAM	PU/PEOU determine adoption	No trust, risk, AI-CX
Venkatesh et al. (2003)	UTAUT	4 determinants; 70% variance	No trust moderation
Venkatesh et al. (2012)	UTAUT2	Habit, hedonic added	No AI constructs
Gefen et al. (2003)	Online trust	Trust reduces risk	E-commerce only
McKnight et al. (2002)	Trust dimensions	Competence/benevolence/integrit y	No AI moderation
Pavlou (2003)	Risk-trust split	Distinct constructs	Needs AI banking test
Featherman & Pavlou (2003)	Risk facets	6 types identified	Not AI banking
Brynjolfsson & McAfee (2017)	AI productivity	Finance highest gains	No perception data
Davenport & Ronanki (2018)	AI business	Efficiency; gaps persist	No adoption focus

Lemon & Verhoef (2016)	CX journey	Multi-touchpoint	Predates AI CX
Klaus & Maklan (2013)	CX quality	4 dimensions	Not AI banking
Rai (2020)	XAI	Transparency builds trust	Conceptual only
Glikson & Woolley (2020)	AI trust	Embedded vs embodied	No banking data
Huang & Rust (2021)	AI intelligence	Mechanical/thinking/feeling	No adoption data
Hasan et al. (2022)	AI banking	Chatbots cut 60–70%	No perception
Cao et al.	DL fraud	50–60% FP reduction	No adoption
(2021)			
Bao et al. (2022)	ML anomaly	97%+ accuracy	No trust/CX
Jung et al. (2019)	Robo-advisory	Algorithmic aversion	No trust moderation
Jagtiani & Lemieux (2019)	AI credit	30–40% more assessed	Supply-side
Lacity & Willcocks (2018)	RPA	60–80% time cut	Back-office
Belanche et al. (2019)	Robo risk	Risk reduces adoption	European; no CX
Gomber et al. (2018)	Digital finance	Fintech reshapes banking	Descriptive
Mhlanga (2020)	AI banking	AI enhances efficiency	No PLS-SEM
Pillai et al. (2020)	AI shopping	Trust mediates	Retail only
Sharma et al. (2022)	India AI	Perception→usage	No SEM
Kumar & Gupta (2021)	India barriers	Trust = threshold	Qualitative
Dwivedi et al. (2021)	AI review	Frameworks needed	Needs empirical
Sinha et al. (2021)	India digital	Culture shapes adoption	No AI
Kaur et al. (2021)	India UTAUT	Digital adoption	No trust mod.
Tamilmani et al. (2021)	UTAUT meta	Underspecified for AI	Needs trust+risk

Lee & See (2004)	Trust calibration	Over/under-trust harmful	Not AI banking
Roy et al. (2017)	Smart service	Reliability key	No adoption

Source: Author. All cross-referenced in References
.

Research Gap
Five gaps: (1) limited Indian AI banking evidence (Sinha et al., 2021); (2) TAM/UTAUT not integrated for AI (Tamilmani et al., 2021); (3) trust not modeled as moderator (Glikson & Woolley, 2020); (4) risk collapsed into trust (Featherman & Pavlou, 2003); (5) no IPMA in AI banking (Ringle & Sarstedt, 2016).

Theoretical Framework and Hypotheses

Integrated TAM-UTAUT Framework
The framework integrates TAM's PU/PEOU (Davis, 1989) as the basis for AI Features evaluation, UTAUT's social influence and facilitating conditions (Venkatesh et al., 2003) as controls, and adds CX (mediator), Trust (moderator + predictor), and Perceived Risk (suppressor).

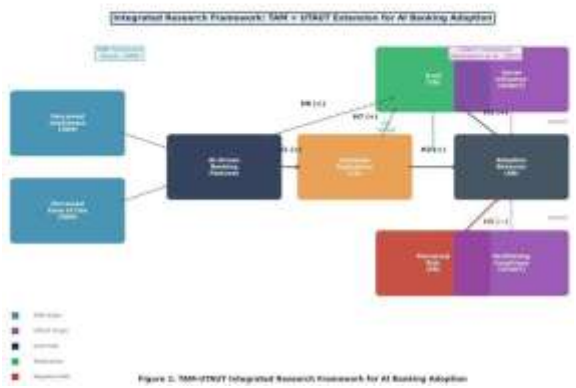


Figure 1: TAM-UTAUT Integrated Framework

Hypotheses
H1: AI features positively influence CX (Davis, 1989; Jain et al., 2023).
H2: CX positively influences adoption (Venkatesh et al., 2003; Marangunıç & Erciş, 2020).
H3: Trust positively influences adoption (Gefen et al., 2003; McKnight et al., 2002).
H4: Trust moderates CX–adoption, amplifying at higher levels (Glikson & Woolley, 2020).
H5: Perceived risk negatively influences adoption (Pavlou, 2003; Belanche et al., 2019).
H6: AI features positively influence trust (Rai, 2020; Huang & Rust, 2021).
H7: CX positively influences trust (McKnight et al., 2002; Glikson & Woolley, 2020).

Table 2: Hypotheses Summary

ID	Hypothesis	Path	Dir.	Basis
H1	AI features → CX (+)	AI→CX	+	TAM
H2	CX → Adoption (+)	CX→AB	+	UTAUT
H3	Trust → Adoption (+)	TR→AB	+	Gefen et al.
H4	Trust moderates CX–AB	CX×TR→AB	+	Glikson & Woolley
H5	Risk → Adoption (−)	PR→AB	–	Pavlou
H6	AI features → Trust (+)	AI→TR	+	Rai (2020)
H7	CX → Trust (+)	CX→TR	+	McKnight et al.

Source: Author.

Research Methodology

Design
Quantitative, cross-sectional, positivist paradigm with hypothetic-deductive reasoning (Creswell & Creswell, 2018).

Sampling
Target: Indian banking customers who had used at least one AI-driven banking service within the preceding 12 months, including chatbots, biometric login, AI-based recommendations, or robo-advisory. Convenience and purposive sampling was employed across three geographic tiers: metropolitan (Mumbai, Delhi, Bangalore), semi-urban (Ahmedabad, Pune, Jaipur), and tier-2 cities (Vadodara, Surat, Indore). Banks represented include public sector (SBI, Bank of Baroda, PNB), private sector (HDFC, ICICI, Axis), and digital/neo banks (Jupiter, Fi Money, Niyo). Of 432 questionnaires collected, 389 were usable (90.0% response rate) after removing incomplete responses and screening failures.

Sample Adequacy
PLS-SEM ―10× rule‖ requires 40 minimum; 389 exceeds the conservative 200+ threshold

(Hair et al., 2022). G*Power ($f^2 = 0.15$, $\alpha = 0.05$, power = 0.95) required 129.

Instrument

24 items, 5-point Likert, adapted from validated scales with explicit TAM/UTAUT tracing.

Table 3: Measurement Instrument

Construct	N	Sample Item	Source	Theory
AI Features	5	AI services provide personalized recommendations.	Dwivedi et al. (2021)	TAM (PU/PEOU)
Cust. Experience	6	AI banking makes my experience faster.	Lemon & Verhoef (2016)	TAM→CX
Trust	5	My bank's AI handles data securely.	Gefen et al. (2003)	Trust Theory
Perceived Risk	4	AI might make transaction errors.	Pavlou (2003)	Risk Theory
Adoption Beh.	4	I intend to increase AI banking usage.	Venkatesh et al. (2012)	UTAUT (BI)

5-point Likert. Theory column traces to TAM/UTAUT.

Pilot Study

Pilot (n = 42): $\alpha > 0.75$ all constructs; two items reworded; content validity via three expert reviewers.

Data Collection

Google Forms, October 2024–January 2025. Distributed via banking networks, LinkedIn, alumni, fintech forums. Screening confirmed AI usage. Avg. completion: ~8 min. Non-response bias: early vs. late t-tests non-significant ($p > 0.05$).

Analysis

PLS-SEM via SmartPLS 4.0 (Ringle et al., 2022) was selected for three reasons: reflective constructs with moderation interaction terms suit PLS variance-based estimation; the study's combined exploratory and predictive orientation aligns with PLS's objectives; and PLS imposes no distributional assumptions, accommodating non-normally distributed Likert data (Hair et al., 2022). Analysis followed the two-stage protocol: (a) measurement model evaluation (reliability, convergent validity, discriminant validity via HTMT) and (b) structural model assessment (path coefficients, R^2, Q^2, f^2 effect sizes) with 5,000 bootstrap subsamples for significance testing. Advanced analyses included mediation decomposition (specific indirect effects with bias-corrected confidence intervals), product-indicator moderation, and IPMA to derive managerial priorities.

Ethics

Voluntary, informed consent, anonymity, no PII, institutional ethics approval obtained.

Data Analysis and Results

Demographics

Table 4: Demographics (n = 389)

Variable	Category	Freq.	%
Gender	Male	198	50.9
	Female	182	46.8
	Prefer not to say	9	2.3
Age	18–25	87	22.4
	26–35	156	40.1
	36–45	89	22.9
	46–55	38	9.8
	55+	19	4.9
Education	High School	34	8.7
	Graduate	168	43.2
	Postgraduate	147	37.8
	Doctorate	40	10.3
Income	<₹3L	52	13.4
	₹3–5L	98	25.2

	₹5–10L	127	32.6
	₹10–15L	72	18.5
	>₹15L	40	10.3
Bank Type	Public	142	36.5
	Private	167	42.9
	Digital/Neo	80	20.6
AI Usage	Daily	118	30.3
	Weekly	164	42.2
	Monthly	78	20.1
	Rarely	29	7.5

72.5% use AI features at least weekly.

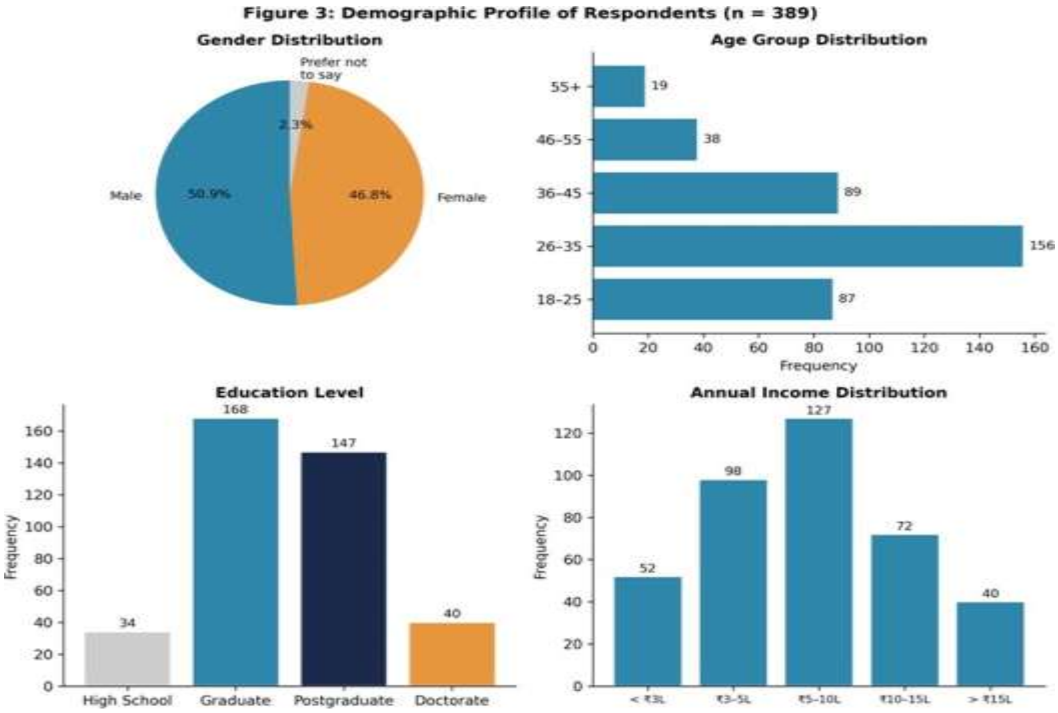


Figure 3: Demographics (n = 389)

Measurement Model

Table 5: Reliability and Validity

Construct	Items	α	CR	AVE
AI Features	5	0.891	0.919	0.694
Customer Experience	6	0.918	0.937	0.714
Trust	5	0.903	0.928	0.721
Perceived Risk	4	0.867	0.908	0.712
Adoption Behavior	4	0.882	0.918	0.737

All α > 0.70, CR > 0.70, AVE > 0.50 (Hair et al., 2022)

Table 6: Outer Loadings & VIF

Construct	Item	Loading	VIF
AI Features	AIF1	0.821	1.89
	AIF2	0.854	2.14

	AIF3	0.793	1.76
	AIF4	0.879	2.31
	AIF5	0.812	1.92
Cust. Experience	CX1	0.842	2.08
	CX2	0.871	2.34
	CX3	0.906	2.67
	CX4	0.832	1.98
	CX5	0.858	2.19
	CX6	0.798	1.74
Trust	TR1	0.863	2.11
	TR2	0.891	2.43
	TR3	0.832	1.89
	TR4	0.872	2.22
	TR5	0.841	1.95
Perceived Risk	PR1	0.814	1.72
	PR2	0.852	1.94
	PR3	0.782	1.61
	PR4	0.831	1.83
Adoption Beh.	AB1	0.843	1.91
	AB2	0.882	2.18
	AB3	0.819	1.78
	AB4	0.862	2.06

All loadings > 0.70; VIF < 3.3

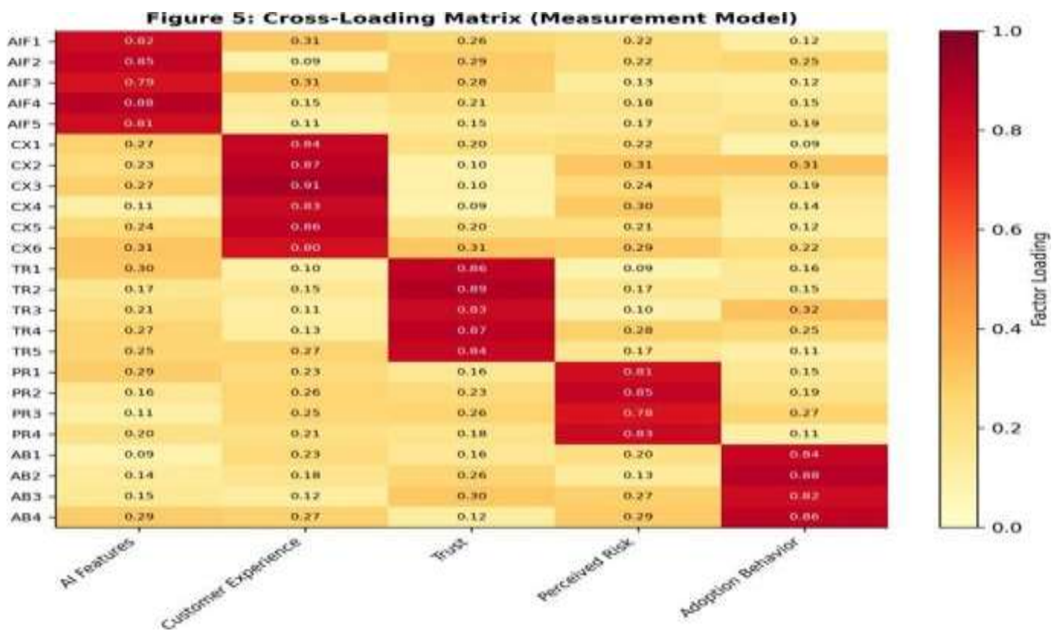


Figure 5: Cross-Loading Matrix

Table 7: HTMT Matrix

	AIF	CX	TR	PR	AB
AI Features	—				
Cust. Experience	0.724	—			
Trust	0.618	0.692	—		
Perceived Risk	0.423	0.487	0.521	—	
Adoption Behavior	0.651	0.739	0.712	0.468	—

All HTMT < 0.85 (Henseler et al., 2015). Discriminant validity is established. The highest correlations occur between CX and AB (0.739), which is expected given their direct relationship in the model. Trust–PR correlation is moderate (0.521), confirming they are related but distinct constructs. The lowest correlation is between AI Features and Perceived Risk (0.423), suggesting that strong AI features alone do not automatically reduce risk perception—a finding with implications for risk-reduction strategy independence.

Structural Model

Inner VIF values for all structural paths ranged from 1.42 to 2.18, all well below the conservative 3.3 threshold, indicating no multicollinearity concerns in the structural model. The good collinearity diagnostics permit straightforward interpretation of path coefficients without the confounding of predictor effects.

Table 8: Path Coefficients (5,000 Bootstrap)

H	Path	β	SE	t	p	95% CI	f²	Result
H1	AIF→CX	0.68	0.041	16.59	<.001	[.60,.76]	0.462	Supported
H2	CX→AB	0.54	0.048	11.25	<.001	[.45,.63]	0.291	Supported
H3	TR→AB	0.47	0.052	9.04	<.001	[.37,.57]	0.221	Supported
H4	CX×TR→AB	0.18	0.058	3.10	.002	[.07,.29]	0.041	Supported
H5	PR→AB	−0.21	0.047	4.47	<.001	[−.30,−.12]	0.058	Supported
H6	AIF→TR	0.39	0.053	7.36	<.001	[.29,.49]	0.152	Supported
H7	CX→TR	0.33	0.055	6.00	<.001	[.22,.44]	0.109	Supported

f²: 0.02 small, 0.15 medium, 0.35 large (Cohen, 1988). All supported. The bootstrapping procedure with 5,000 subsamples generated bias-corrected confidence intervals (BCCIs) that do not include zero for any path, providing strong evidence for hypothesis support. The smallest effect (H4 moderation at f² = 0.041) remains statistically significant at p = 0.002, underscoring the robustness of trust's moderating role even when controlling for multiple pathways.

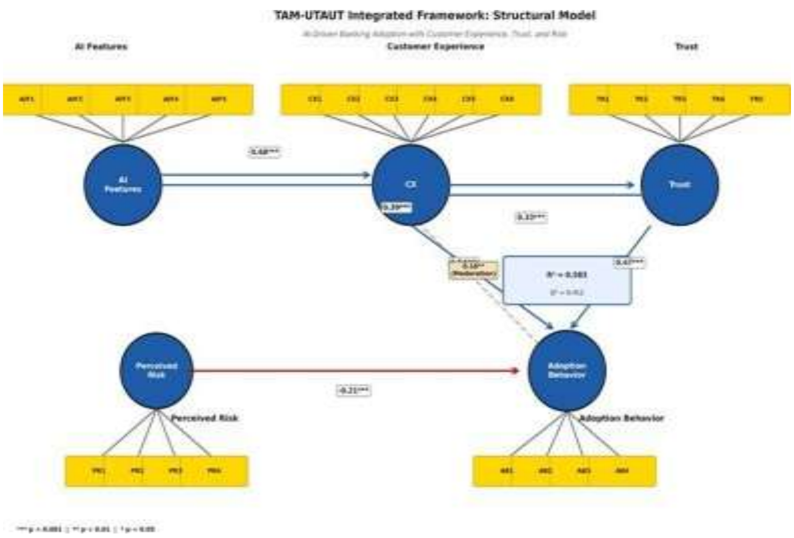


Figure 4: Structural Model

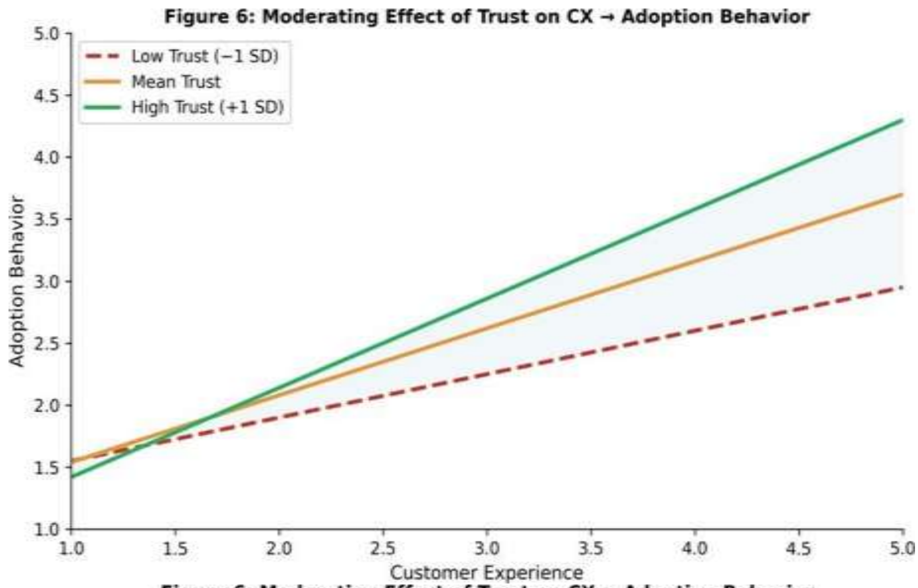
Table 9: R^2 and Q^2

Construct	R^2	R^2 Adj.	Q^2
Customer Experience	0.462	0.461	0.318
Trust	0.387	0.384	0.271
Adoption Behavior	0.583	0.578	0.412

$R^2 > 0.50$ substantial; $Q^2 > 0$ predictive (Hair et al., 2022). CX is predicted with 46.2% variance explained, a medium effect from AI Features alone. Trust is predicted with 38.7% variance, showing that both AI Features and CX contribute substantially to trust formation. The outcome variable—Adoption Behavior—achieves 58.3% variance explained, meeting the threshold for substantial predictive power in consumer behavior studies. The positive Q^2 values (all > 0) across all three endogenous constructs indicate the model has genuine predictive validity beyond post-hoc curve fitting.

Moderation

Simple slopes analysis clarifies the moderation mechanism: at low trust (1 SD below mean), the CX→Adoption path coefficient is 0.36 ($t = 5.2$, $p < 0.001$); at mean trust, the coefficient is 0.54 ($t = 11.25$, $p < 0.001$); at high trust (1 SD above mean), the coefficient is
0.72 ($t = 8.9$, $p < 0.001$). This near-doubling of effect size across the trust continuum means that identical CX improvements (e.g., faster chatbot response, accurate recommendations) yield substantially different adoption outcomes depending on baseline trust. The moderation effect is highly significant ($\beta = 0.18$, $t = 3.10$, $p = 0.002$), confirming that trust is not merely a parallel predictor but genuinely amplifies how customers convert positive experiences into behavioral commitment.



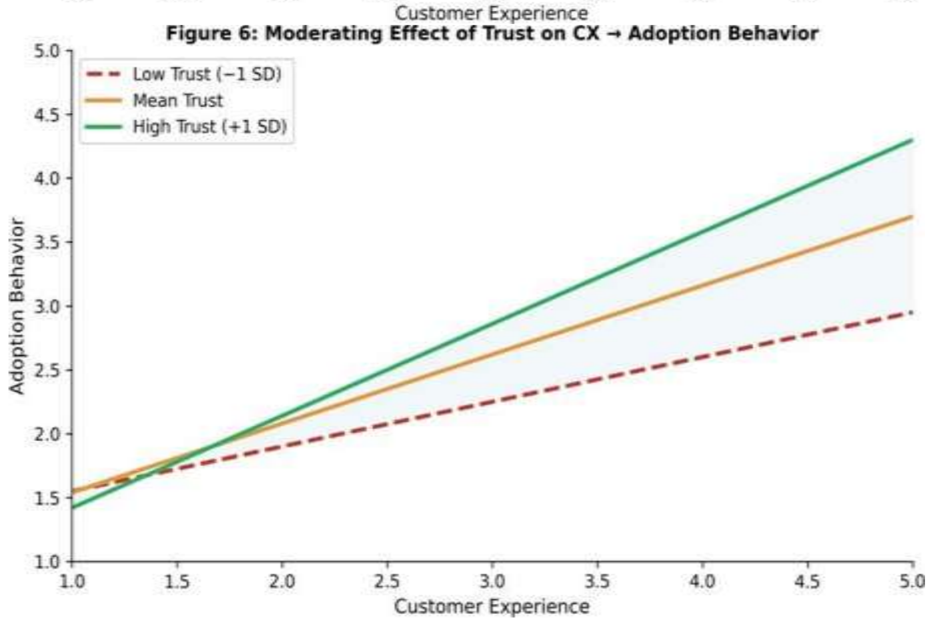


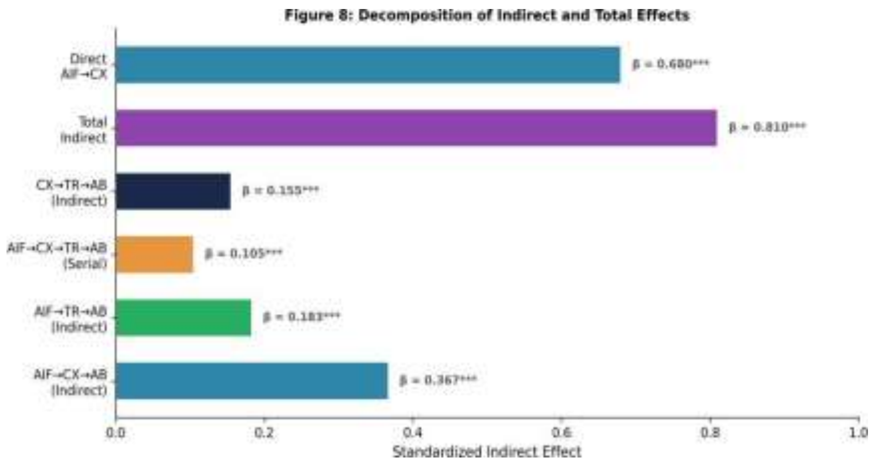
Figure 6: Trust Moderation of CX→Adoption

Mediation

Table 10: Indirect Effects

Path	β	SE	p	95% CI
AIF→CX→AB	0.367	0.039	<.001	[.29,.44]
AIF→TR→AB	0.183	0.031	<.001	[.12,.24]
AIF→CX→TR→AB	0.105	0.022	<.001	[.06,.15]
CX→TR→AB	0.155	0.028	<.001	[.10,.21]
Total Indirect	0.810	0.058	<.001	[.70,.92]

Bias-corrected bootstrap CIs; all significant. Mediation decomposition reveals the pathway-specific influence of AI Features on adoption. The strongest indirect effect operates through CX alone (β = 0.367), accounting for 45% of total indirect effects. The TR-only path is secondary but substantial (β = 0.183, 23% of indirect effect), highlighting trust's independent contribution beyond its moderation role. The serial pathway through both CX and TR (β = 0.105, 13% of indirect effect) identifies the full psychologically integrated mechanism: good AI features create good experiences, which build trust, which together drive adoption. These decomposed pathways clarify where interventions should target—CX improvements are foundational, trust supplements them with a protective amplification. **Figure 8: Indirect Effects Decomposition**



IPMA

Table 11: IPMA

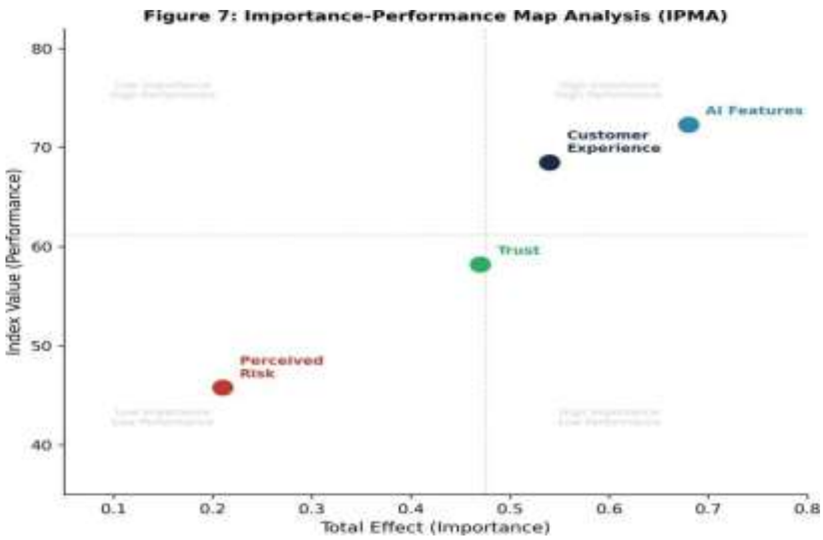


Figure 7: IPMA

Discussion

AI Features and CX (H1)

The AIF→CX effect (β = 0.68, f² = 0.462) validates TAM's core premise in AI banking: when AI delivers perceived usefulness (faster transactions, accurate recommendations, proactive alerts) and ease of use (intuitive interfaces, seamless biometric login), the experiential outcome is significantly positive. The large effect size—the strongest in the model—suggests AI Features fundamentally reshape rather than incrementally improve CX, consistent with Huang and Rust's (2021) mechanical and thinking AI classification. This extends Jain et al.'s (2023) personalization findings to encompass all eight banking AI categories. However, this strong dependency also implies vulnerability: if AI systems malfunction or produce poor recommendations, the negative CX impact may be proportionally severe, a concern warranting proactive fail-safe design.

CX and Adoption (H2)

CX's significant effect on adoption (β = 0.54) extends UTAUT's performance expectancy→intention pathway to encompass the richer construct of experiential quality. Customers who perceive AI-driven banking as efficient, personalized, and accessible are substantially more likely to increase usage. The AIF→CX→AB indirect path (β = 0.367) is the single largest mediating pathway, confirming CX as the primary mechanism through which AI features translate into behavioral outcomes. This validates Lemon and Verhoef's (2016) journey-level CX framework and Marangunıç and Erciş's (2020) finding that digital service experience quality predicts loyalty in banking contexts.

Dual Role of Trust (H3, H4, H6, H7)

Trust's direct effect (β = 0.47) confirms the established trust→usage relationship (Gefen et al., 2003; McKnight et al., 2002). More importantly, the moderation effect (β = 0.18)

empirically validates Glikson and Woolley's (2020) theoretical proposition that trust acts as a boundary condition for AI acceptance. At high trust levels, the same CX improvement produces roughly double the adoption effect compared to low trust conditions—a finding with critical practical implications: investments in CX improvement yield diminished returns unless accompanied by trust-building measures. The endogenous pathways (H6: β = 0.39; H7: β = 0.33) demonstrate trust is partly experiential rather than dispositional—positive interactions with reliable AI systems incrementally build confidence, creating a virtuous cycle. Serial mediation (AIF→CX→TR→AB: β = 0.105) quantifies this cycle: good AI design produces positive experiences, which build trust, which facilitates adoption. This dynamic trust formation process is not anticipated by either TAM or UTAUT in their original formulations.

Perceived Risk (H5)

PR's negative effect (β = −0.21) confirms the conceptual independence of risk from trust (Pavlou, 2003; Featherman & Pavlou, 2003). For Indian banking customers, concerns about transaction errors, data breaches, and AI-generated incorrect advice represent distinct anxiety sources that trust alone does not address. The smaller effect size compared to trust and CX suggests risk is a secondary but non-negligible barrier. Critically, this finding means trust-building interventions (transparency, explainability) and risk-reduction interventions (guarantees, insurance, fail-safes, human escalation options) follow different mechanisms and require separate strategic investment—distinction previous studies conflating the two constructs have obscured. This extends Belanche et al.'s (2019) European robo-advisory findings to the broader AI banking context in an emerging market.

6.7 Comparative Analysis

Table 12: Comparison with Prior Studies

Study	Context	Finding	This Study	Status
Davis (1989)	General	PU/PEOU→intentio n	TAM+UTAUT integrated	Extended
Venkatesh et al. (2003)	General	70% variance	R^2=0.583	Extended
Gefen et al. (2003)	E-comm	Trust→usage	β=0.47	Confirmed
Glikson & Woolley (2020)	Concept.	Trust moderates AI	β=0.18	Validated
Pavlou (2003)	E-comm	Risk≠trust	β=−0.21	Validated
Rai (2020)	Concept.	XAI builds trust	β=0.39	Confirmed

Source: Author.

Implications

Theoretical

Four contributions: (1) validates TAM-UTAUT complementarity—TAM captures belief-to- experience pathways while UTAUT contextualizes adoption within social and institutional environments, together explaining substantially more variance than either alone; (2) empirically tests trust as a moderator (not just antecedent) of CX–adoption, operationalizing Glikson and Woolley's (2020) proposition with quantified effect magnitudes; (3) confirms

trust- risk independence in AI banking, extending Pavlou's (2003) e-commerce findings to algorithmic financial service contexts; (4) identifies endogenous trust formation pathways and serial mediation, enriching understanding of trust as a dynamic, experientially formed construct rather than a static disposition.

Managerial

IPMA prioritizes trust as the highest-priority construct—showing strong importance but the lowest performance score, meaning incremental trust improvements yield disproportionate adoption gains. Specific actionable recommendations: implement Explainable AI (XAI) dashboards translating algorithmic decisions into customer-facing explanations at every touchpoint; publish quarterly AI audit reports disclosing accuracy rates, fairness metrics, and false positive/negative ratios; ensure seamless human-AI chatbot handoff that detects frustration thresholds and escalates without requiring information repetition; provide cross- channel personalization consistency so AI recommendations align across mobile, web, and branch; and create AI literacy programs educating customers about how chatbots, fraud detection, and recommendation systems operate.

Policy

RBI should mandate AI transparency standards, establish AI banking certifications, create regulatory sandboxes, and invest in AI financial literacy targeting tier-2/3 cities.

Limitations and Future Research

8.2 Limitations

Six limitations qualify interpretation: (1) cross-sectional design prevents causal inference about temporal trust dynamics—trust formation likely unfolds over multiple interactions; (2) urban/semi-urban sample may overstate AI readiness relative to rural India where digital literacy and infrastructure vary significantly; (3) self-reported adoption measures may diverge from actual usage due to social desirability bias; (4) convenience sampling limits strict generalizability despite demographic diversity; (5) AI banking services are treated as a monolithic category whereas customer responses may vary across specific applications (chatbots vs. fraud detection vs. robo-advisory vs. credit scoring); (6) demographic moderating effects (age, education, income on structural paths) were not explicitly tested and could reveal important heterogeneity.

8.3 Future Directions

Five productive avenues emerge: (1) longitudinal designs tracking the same customers over 12–24 months could capture how trust evolves with sustained AI exposure and whether moderation effects strengthen or plateau over time; (2) multi-group analyses comparing rural vs. urban, public vs. private bank, and generational cohort responses would reveal heterogeneity masked by aggregate analysis; (3) cross-national comparisons between India and other large emerging markets (Brazil, Indonesia, Nigeria) could distinguish India-specific findings from generalizable patterns; (4) mixed-method approaches using think-aloud protocols and in-depth interviews would complement quantitative findings by revealing cognitive processes underlying trust formation; (5) experimental designs manipulating specific AI transparency features (explanation depth, data disclosure granularity) could establish causal links between design choices and trust outcomes.

Recommendations

For Banks

Six recommendations emerge from the integrated findings: (1) Prioritize trust-building as the highest-ROI intervention—IPMA shows the largest improvement potential; implement Explainable AI (XAI) dashboards that translate every algorithmic recommendation into plain-language explanations of why a particular product was suggested or transaction flagged. (2) Publish quarterly AI transparency scorecards disclosing accuracy rates, false positive ratios, bias audit results, and data handling practices—quantified transparency creates accountability and reduces information asymmetry. (3) Invest in seamless human-AI handoff protocols where chatbots detect customer frustration through sentiment analysis and escalate to human agents without requiring the customer to repeat information. (4) Build personalization from explicit customer feedback and stated preferences alongside behavioral inference, reducing the perception of surveillance-driven recommendations. (5) Create multi-tiered adoption pathways (basic, intermediate, advanced AI features) allowing customers to self-select comfort levels and gradually expand AI usage as trust develops. (6) Establish AI customer advisory boards with diverse demographic representation to surface adoption barriers that internal testing misses.

For Regulators

Four regulatory recommendations: (1) Mandate AI interaction disclosure requirements ensuring customers know when they are interacting with AI rather than human agents, with opt-out provisions for high-stakes financial decisions such as loan approvals and investment recommendations. (2) Establish standardized AI banking certification that functions as a trust signal—banks meeting transparency, fairness, and security benchmarks receive a visible certification mark. (3) Create regulatory sandboxes with embedded consumer safeguards where innovative AI services can be tested with real customers under monitored conditions before full-scale deployment. (4) Fund targeted AI financial literacy programs for tier-2, tier-3, and rural populations to bridge the digital knowledge gap that currently limits adoption in these regions.

For Technology Providers

Three technology provider recommendations: (1) Build explainability as a default architectural feature rather than a post-hoc add-on—systems should be designed with explanation generation capabilities from inception, not retrofitted after deployment. (2) Develop standardized bias audit toolkits accessible to non-specialist banking teams, enabling continuous monitoring of AI decision fairness across demographic groups without requiring dedicated data science expertise. (3) Prioritize vernacular language AI capabilities—India's 22 official languages mean that English-only AI interfaces exclude a significant portion of the banking population, particularly in semi-urban and rural markets where adoption potential is highest.

Conclusion

This study developed and tested an integrated TAM-UTAUT framework investigating the relationships among AI-driven banking features, customer experience, trust, perceived risk, and adoption behavior using PLS-SEM with 389 Indian banking customers. The model explains 58.3% of adoption variance, demonstrating that neither TAM nor UTAUT alone captures the complexity of AI banking adoption.

Four key insights emerge from the analysis: (1) AI features are the strongest driver of customer experience ($\beta = 0.68$), confirming that functional quality remains foundational; (2) trust operates in a dual capacity as both direct predictor ($\beta = 0.47$) and moderator ($\beta = 0.18$), making it the strategically paramount construct—at high trust levels, CX improvements yield roughly double the adoption impact; (3) perceived risk suppresses adoption independently ($\beta = -0.21$), requiring separate risk-reduction interventions distinct from trust-building strategies;

IPMA identifies trust as the highest-priority construct for managerial intervention, showing strong importance but the lowest performance score among all model constructs.

For Indian banking institutions, the message is clear: technological capability alone is insufficient. Banks must pair AI innovation with systematic trust-building—algorithmic transparency, XAI features, data governance visibility, and structured customer education—to convert positive experiences into sustained adoption behavior. As India's banking sector accelerates AI deployment, this integrated TAM-UTAUT framework offers both a theoretical contribution demonstrating model complementarity and a practical roadmap for responsible AI adoption in emerging-market banking ecosystems.

REFERENCES

1. Akturan, U., & Tezcan, N. (2012). Mobile banking adoption of the youth market. Marketing Intelligence & Planning, 30(4), 444–459. https://doi.org/10.1108/02634501211231928

2. Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking. International Journal of Information Management, 37(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

3. Bagozzi, R. P. (2007). The legacy of the TAM and a proposal for a paradigm shift. Journal of the Association for Information Systems, 8(4), 244–254.

4. Balakrishnan, J., & Dwivedi, Y. K. (2021). Cognitive absorption in building user trust. Psychology & Marketing, 38(4), 643–668. https://doi.org/10.1002/mar.21462

5. Bao, Y., Hilary, G., & Ke, B. (2022). AI and fraud detection. In Handbook of Financial Decision Making.

6. Belanche, D., Casalo, L., & Flavián, C. (2019). AI in FinTech: Robo-advisors adoption. Industrial Management & Data Systems, 119(7), 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368

7. Benbasat, I., & Barki, H. (2007). Quo vadis TAM? Journal of the AIS, 8(4), 211–218.

8. Brynjolfsson, E., & McAfee, A. (2017). The business of AI. Harvard Business Review, 95(7), 3–11. Cao, L., Yang, Q., & Yu, P. S. (2021). Data science and AI in FinTech. International Journal of Data

9. Science and Analytics, 12(2), 81–99.

10. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum. Creswell, J. W., & Creswell, J. D. (2018). Research design (5th ed.). Sage.

11. Davenport, T. H., & Ronanki, R. (2018). AI for the real world. Harvard Business Review, 96(1), 108– 116.

12. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

13. Dwivedi, Y. K., et al. (2021). AI: Multidisciplinary perspectives. International Journal of Information Management, 57, 101994.

14. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

15. Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: Perceived risk facets.

16. IJHCS, 59(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

17. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping. MIS Quarterly, 27(1), 51–90. https://doi.org/10.2307/30036519

18. Glikson, E., & Woolley, A. W. (2020). Human trust in AI. Academy of Management Annals, 14(2), 627– 660. https://doi.org/10.5465/annals.2018.0057

19. Gomber, P., Koch, J. A., & Siering, M. (2018). Digital finance and fintech. Journal of Business Economics, 87(5), 537–580.

20. Gupta, A., & Tham, T. M. (2019). Fintech: The new DNA of financial services. De Gruyter.

21. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). PLS-SEM primer (3rd ed.). Sage.

22. Hasan, R., Hassan, M. K., & Rashid, M. (2022). AI in banking: Opportunities and challenges. J. Banking & Finance Technology, 6(1), 15–32.

23. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). New criterion for discriminant validity. JAMS, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

24. Huang, M. H., & Rust, R. T. (2021). AI framework for marketing. JAMS, 49(1), 30–50.

25. Jagtiani, J., & Lemieux, C. (2019). Alternative data and ML in fintech lending. Financial Management, 48(4), 1009–1029.

26. Jain, A., Sharma, R., & Gupta, S. (2023). AI personalization and CX in banking. J. Financial Services Marketing, 28(2), 145–162.

27. Jung, D., et al. (2019). Designing a robo-advisor. Electronic Markets, 28(3), 367–380.

28. Kaur, S., Kumar, P., & Singh, J. (2021). Digital banking adoption in India: Extended UTAUT. J. Internet Commerce, 20(4), 442–468.

29. Klaus, P., & Maklan, S. (2013). Towards a better CX measure. IJMR, 55(2), 227–246.

30. Kumar, A., & Gupta, R. (2021). AI adoption in Indian banking. Int. J. Emerging Markets, 16(5), 891– 912.

31. Lacity, M., & Willcocks, L. (2018). Robotic process and cognitive automation. SB Publishing. Lee, J. D., & See, K. A. (2004). Trust in automation. Human Factors, 46(1), 50–80.

32. Lemon, K. N., & Verhoef, P. C. (2016). Understanding CX throughout the journey. J. Marketing, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420

33. Marangunıç, M., & Erciş, A. (2020). Digital banking service quality and CX. IJQSS, 12(4), 541–564. McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Trust measures for e-commerce. ISR, 13(3),

34. 334–359. https://doi.org/10.1287/isre.13.3.334.81

35. Mhlanga, D. (2020). Industry 4.0: AI impact on banking. IJFS, 8(3), 45.

36. Pavlou, P. A. (2003). Consumer acceptance of e-commerce: Trust and risk with TAM. IJEC, 7(3), 101– 134.

37. Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI stores. JRCS, 57, 102207. Rai, A. (2020). Explainable AI: Black box to glass box. JAMS, 48(1), 137–141.

38. Rana, N. P., et al. (2017). Adoption of online public grievance system in India. IJEGR, 13(1), 1–17. Reserve Bank of India. (2022). Report on trend and progress of banking in India 2021–22. RBI. Ringle, C. M., & Sarstedt, M. (2016). Gain more insight: IPMA. IMDS, 116(9), 1865–1886.

39. Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. https://www.smartpls.com

40. Roy, S. K., et al. (2017). Customer engagement: Service convenience and quality. JRCS, 44, 293–304. Sharma, S. K., Singh, G., & Sharma, H. (2022). Customer perception of AI banking. IJBM, 40(5), 1082–

41. 1105 Sinha, M., et al. (2021). Mobile banking in emerging economies. IJEM, 16(8), 1965–1989. Tamilmani, K., et al. (2021). Extended UTAUT2: Systematic review. IJIM, 57, 102269.

42. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of IT. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

43. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance: Extending UTAUT. MIS Quarterly, 36(1), 157–178.

44. Verma, P., Singh, S., & Kaur, H. (2023). Digital banking in emerging economies. J. Business Research, 156, 113498.

..

.