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A Multi-Group Analysis of Artificial Intelligence Adoption in Financial Services, Technology Acceptance, Perceived Risk, and the Mediating Role of Trust.

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Abstract

Artificial intelligence (AI) is transforming financial services through automated credit scoring, robo-advisory, fraud detection, and personalized financial product recommendation. However, consumer adoption of AI-driven financial services remains uneven across demographic and national contexts, presenting a critical challenge for financial service providers and policymakers. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT2), this study examines the antecedents of AI adoption intention in financial services, incorporating perceived risk and consumer trust as mediating variables. A multi-group analysis (MGA) compares adoption dynamics across Nigeria, Mexico, and India—three large emerging economies at different stages of fintech development. Survey data from 468 financial service consumers were analyzed using covariance-based structural equation modeling (CB-SEM) in AMOS 27. Results reveal that performance expectancy (β = 0.391), effort expectancy (β = 0.287), and social influence (β = 0.234) significantly predict AI adoption intention, with trust mediating all three relationships. Perceived risk exerts a significant negative effect on AI adoption intention (β = −0.312, $p < 0.001$), partially mitigated by trust (indirect effect = −0.187). Multi-group analysis reveals significant cross-country heterogeneity: performance expectancy dominates in India, social influence dominates in Nigeria, and effort expectancy is paramount in Mexico. These findings advance UTAUT2 theory in AI financial service contexts and provide differentiated strategic implications for fintech adoption programs across emerging markets.

Keywords: artificial intelligence, financial services, technology acceptance, UTAUT2, consumer trust, perceived risk, multi-group analysis

1. Introduction

The integration of artificial intelligence into financial services has catalyzed one of the most significant structural transformations in the history of the banking and finance industry. AI applications in financial services now span credit scoring automation, robo-advisory wealth management, real-time fraud detection, AI-powered insurance underwriting, personalized product recommendation engines, and conversational banking through natural language processing interfaces (Cao, 2022; Lee & Shin, 2018). The global fintech AI market was valued at approximately USD 44.08 billion in 2024 and is projected to grow at a compound annual growth rate exceeding 25% through 2030, driven by both technological advancement and shifting consumer preferences (MarketsandMarkets, 2024). Yet, consumer adoption of these AI-driven services remains heterogeneous, creating a critical gap between technological capability and market penetration.

Understanding the behavioral determinants of AI adoption in financial services is particularly consequential in emerging market economies, which simultaneously present the largest potential user bases and the greatest adoption barriers. Nigeria, with approximately 83 million unbanked adults, has witnessed explosive mobile money and fintech growth, driven by regulatory innovation (e.g., Central Bank of Nigeria's fintech licensing framework) and technology-forward consumer segments (GSMA, 2023). Mexico's financial inclusion agenda—centered on the CoDi and DiMo payment platforms and an open banking regulatory framework—has created significant AI adoption opportunities in underserved rural and semi-urban populations (World Bank, 2022). India's UPI ecosystem, JAM trinity (Jan Dhan-Aadhaar-Mobile), and SEBI's regulatory sandbox for robo-advisory have positioned India as a global leader in financial technology democratization, with AI adoption in retail banking accelerating dramatically (NPCI, 2023).

Despite this rich contextual backdrop, empirical research on AI adoption in financial services remains concentrated in developed economy contexts—particularly the United States, United Kingdom, and China—while large-sample empirical evidence from African, Latin American, and South Asian markets is conspicuously sparse (Lim et al., 2021; Teo et al., 2022). This geographical lacuna is particularly problematic given evidence that cultural, institutional, and economic contextual factors substantially shape technology adoption dynamics (Hofstede, 2011; Venkatesh et al., 2012).

The Unified Theory of Acceptance and Use of Technology (UTAUT), originally developed by Venkatesh et al. (2003) and extended to consumer contexts as UTAUT2 by Venkatesh et al. (2012), provides the dominant theoretical framework for technology adoption research. UTAUT2 identifies performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit as core adoption determinants. However, the application of UTAUT2 to AI-specific financial service contexts necessitates theoretical augmentation to capture AI-specific constructs—particularly perceived risk and consumer trust, which assume heightened importance when consumers entrust consequential financial decisions to algorithmic systems (Belanche et al., 2019; Szopiński, 2016).

Perceived risk in AI financial services encompasses technology malfunction risk, data privacy risk, financial loss risk, and algorithmic bias risk—dimensions that are qualitatively distinct from risks associated with conventional digital financial services (Featherman & Pavlou, 2003; Lim et al., 2021). Consumer trust, in this context, encompasses both competence-based trust (confidence in AI's technical capability) and benevolence-based trust (confidence in the organization's intentions to act in the consumer's interest) (Mayer et al., 1995; Belanche et al., 2019). These constructs mediate the relationships between UTAUT2 antecedents and adoption intention by determining whether consumers translate positive technology perceptions into actual behavioral commitments.

The present study makes four principal contributions. First, it extends UTAUT2 to the AI financial services adoption context with perceived risk and trust as mediating variables. Second, it provides large-sample empirical evidence from three major emerging economies, addressing the geographical gap in AI adoption research. Third, multi-group analysis reveals cross-country heterogeneity in adoption dynamics, generating contextually differentiated insights. Fourth, the study provides a nuanced understanding of how trust mitigates perceived risk in AI adoption decisions.

2. Literature Review

2.1 UTAUT2 in Financial Technology Contexts

The UTAUT2 framework represents the most comprehensive and empirically validated theoretical platform for studying technology adoption in consumer markets. Venkatesh et al. (2012) validated UTAUT2 across three longitudinal waves with 1,512 participants, demonstrating its superior explanatory power ($R^2 = 0.74$ for behavioral intention) relative to TAM, TPB, and eight other competing frameworks. In financial technology contexts, UTAUT2 has been applied to mobile banking (Yu, 2012), contactless payments (Oliveira et al., 2016), cryptocurrency adoption (Teo et al., 2022), and robo-advisory services (Belanche et al., 2019). Performance expectancy—the degree to which AI financial services enhance financial task performance—consistently emerges as the strongest adoption predictor across contexts (Yu, 2012; Oliveira et al., 2016).

Effort expectancy captures the perceived ease of using AI financial service interfaces, reflecting the cognitive and operational costs of technology adoption (Venkatesh et al., 2012). Social influence—reflecting the degree to which important reference individuals endorse AI financial service use—is particularly salient in collectivist cultural contexts (Hofstede, 2011), suggesting cross-cultural heterogeneity in its relative importance. Facilitating conditions represent the availability of technical infrastructure and organizational support that enable AI service use, a dimension of particular relevance in emerging markets with uneven digital infrastructure quality.

2.2 Perceived Risk in AI Financial Services

Risk perceptions constitute a critical attitudinal barrier to technology adoption,

particularly for services involving consequential, personalized, and data-intensive transactions (Featherman & Pavlou, 2003). Perceived risk in AI financial services is multidimensional, encompassing performance risk (accuracy of AI recommendations), financial risk (potential monetary losses from AI errors), privacy risk (unauthorized data use), and social risk (perceived social disapproval of AI financial service use) (Lim et al., 2021). Uniquely, AI contexts introduce algorithmic risk—concerns about opaque decision-making processes, bias, and lack of human accountability—that conventional technology risk models do not adequately capture (Cao, 2022). Meta-analytic evidence from Featherman and Pavlou (2003) confirms that perceived risk consistently negatively predicts adoption intentions, with privacy risk and financial risk demonstrating the strongest effects.

2.3 Consumer Trust in AI Systems

Consumer trust in AI financial services has emerged as a pivotal construct bridging technology perception and adoption behavior (Belanche et al., 2019; Mayer et al., 1995). Mayer et al.'s (1995) foundational trust model identifies ability, benevolence, and integrity as the three pillars of interpersonal trust, each adaptable to AI-consumer trust contexts. Competence-based AI trust reflects confidence in the system's technical ability to provide accurate, reliable financial guidance. Integrity-based trust reflects perceptions of algorithmic fairness and transparency. Benevolence-based trust reflects confidence in the provider's commitment to consumer welfare rather than profit maximization. Glikson and Woolley (2020) demonstrated through experimental evidence that transparency mechanisms significantly enhance AI trust by making algorithmic reasoning interpretable to lay users.

In the UTAUT2 context, trust functions as a mediator between positive technology perceptions (performance expectancy, effort expectancy, social influence) and behavioral adoption intention (Szopiński, 2016). Consumers who perceive AI financial services as capable, easy to use, and socially endorsed are more likely to develop trust in these systems, which in turn strengthens adoption intentions. Concurrently, trust mitigates perceived risk by providing a cognitive and affective buffer against uncertainty (Pavlou, 2003).

2.4 Cross-Cultural Dimensions of Technology Adoption

Multi-group analysis in technology adoption research has consistently revealed that cultural dimensions shape the relative importance of UTAUT2 constructs (Hofstede, 2011; Venkatesh et al., 2012). Specifically, power distance influences deference to social influence in adoption decisions; individualism versus collectivism shapes the relative weight of personal utility versus social norms; uncertainty avoidance affects the salience of risk perceptions; and long-term orientation influences habitual versus deliberative adoption pathways. Nigeria's high power distance and collectivism suggest elevated social influence on AI adoption. Mexico's high uncertainty avoidance implies greater sensitivity to perceived risk and effort expectancy. India's long-term orientation and moderate individualism suggest performance expectancy primacy. These cultural-theoretical predictions motivate the multi-group analysis design.

2.5 Integration and Theoretical Framework

The integrated framework positions performance expectancy, effort expectancy, and social influence as antecedents of AI adoption intention, with trust mediating each relationship. Perceived risk operates as both a direct negative predictor of adoption intention and a variable partially mitigated by trust. Multi-group analysis tests whether these structural relationships vary significantly across the three country contexts.

3. Research Gap

Three gaps motivate this study. First, UTAUT2 has not been systematically extended to AI-specific financial services with trust and perceived risk as joint mediators in emerging market contexts. Second, multi-group analysis comparing AI adoption dynamics across Nigeria, Mexico, and India—representing Africa, Latin America, and South Asia respectively—has not been conducted, limiting understanding of cross-regional heterogeneity. Third, the trust-as-risk-mitigator mechanism in AI financial service adoption has been theorized (Pavlou, 2003) but not empirically validated in large-sample emerging market studies.

4. Research Objectives

RO1: To examine the direct effects of UTAUT2 constructs (performance expectancy, effort expectancy, social influence) on AI adoption intention in financial services.

RO2: To investigate the mediating role of consumer trust in these relationships.

RO3: To assess the direct and trust-mediated effects of perceived risk on AI adoption intention.

RO4: To compare structural model relationships across Nigeria, Mexico, and India using multi-group analysis.

5. Hypotheses Development

H1a–c: Performance expectancy (H1a), effort expectancy (H1b), and social influence (H1c) positively predict AI adoption intention in financial services.

H2a–c: Consumer trust mediates the relationships between performance expectancy (H2a), effort expectancy (H2b), social influence (H2c) and AI adoption intention.

H3: Perceived risk negatively predicts AI adoption intention.

H4: Consumer trust mediates the negative relationship between perceived risk and AI adoption intention.

H5: Structural relationships vary significantly across Nigeria, Mexico, and India (multi-group moderation).

6. Research Methodology

6.1 Design and Sample

A cross-sectional survey was administered to financial service consumers in Nigeria (n = 156), Mexico (n = 157), and India (n = 155) who had used or were considering using AI-powered financial services (mobile banking with AI features, robo-advisory, AI chatbots). Stratified random sampling ensured representation across age, income, and urban/rural categories. Final usable sample: N = 468 after data cleaning.

6.2 Measurement Instruments

Performance Expectancy (4 items), Effort Expectancy (4 items), and Social Influence (4 items) were adapted from Venkatesh et al. (2012). Perceived Risk was measured using Featherman and Pavlou's (2003) 6-item scale adapted for AI contexts. Consumer Trust was assessed using Mayer et al.'s (1995) framework adapted by Belanche et al. (2019) into a 9-item scale. AI Adoption Intention was measured using a 5-item behavioral intention scale. All items used seven-point Likert scales.

6.3 Analysis

CB-SEM in AMOS 27 with full information maximum likelihood (FIML) for missing data. Measurement invariance established through configural, metric, and scalar invariance tests prior to MGA. Mediation tested using bootstrapping in AMOS with 5,000 iterations. Pairwise group comparisons (Nigeria vs. Mexico, Mexico vs. India, Nigeria vs. India) conducted using chi-square difference tests.

7. Data Analysis and Findings

7.1 Demographic Profile

Table 1 *Demographic Profile (N = 468)*

Variable	Category	Nigeria	Mexico	India	Total
Gender	Male	84 (53.8%)	79 (50.3%)	88 (56.8%)	251 (53.6%)
	Female	72 (46.2%)	78 (49.7%)	67 (43.2%)	217 (46.4%)
Age	18–24	31 (19.9%)	28 (17.8%)	34 (21.9%)	93 (19.9%)
	25–34	58 (37.2%)	61 (38.9%)	63 (40.6%)	182 (38.9%)
	35–44	42 (26.9%)	46 (29.3%)	38 (24.5%)	126 (26.9%)
	45+	25 (16.0%)	22 (14.0%)	20 (12.9%)	67 (14.3%)
Education	Below degree	29 (18.6%)	34 (21.7%)	22 (14.2%)	85 (18.2%)
	Degree	79 (50.6%)	78 (49.7%)	81 (52.3%)	238 (50.9%)
	Postgraduate	48 (30.8%)	45 (28.7%)	52 (33.5%)	145 (31.0%)

7.2 Measurement Model (CFA)

Table 2 *Reliability and Validity (Full Sample, N = 468)*

Construct	Items	α	CR	AVE	Loadings
Performance Expectancy (PE)	4	0.871	0.896	0.683	0.784–0.861
Effort Expectancy (EE)	4	0.854	0.882	0.654	0.762–0.839
Social Influence (SI)	4	0.843	0.874	0.635	0.741–0.828
Perceived Risk (PR)	6	0.886	0.907	0.621	0.724–0.846
Trust (TR)	9	0.912	0.928	0.638	0.732–0.879
AI Adoption Intention (AI)	5	0.893	0.914	0.681	0.783–0.867

Table 3 *Model Fit (CFA)*

Index	Value	Threshold
χ^2/df	2.23	< 3.00
CFI	0.947	> 0.90
TLI	0.942	> 0.90
RMSEA	0.051	< 0.08
SRMR	0.049	< 0.08

Measurement Invariance: Configural (CFI = 0.947), metric (ΔCFI = −0.007), and scalar (ΔCFI = −0.009) invariance established, supporting multi-group comparisons.

7.3 Correlation Matrix

Table 4 *Correlations and Descriptive Statistics (Full Sample)*

	M	SD	PE	EE	SI	PR	TR	AI
PE	4.93	1.21	—					
EE	4.67	1.18	0.489***	—				
SI	4.54	1.24	0.412***	0.398***	—			
PR	3.12	1.31	−0.367***	−0.421***	−0.289***	—		
TR	4.71	1.17	0.563***	0.512***	0.487***	−0.542***	—	
AI	4.82	1.23	0.589***	0.481***	0.423***	−0.524***	0.641***	—

Note. *** p < 0.001.

7.4 Structural Model: Full Sample

Table 5 *Structural Path Results (Full Sample, N = 468)*

Path	β	SE	t	p	Decision
PE → Trust	0.412	0.053	7.774	0.000	—
EE → Trust	0.347	0.056	6.196	0.000	—

Path	β	SE	t	p	Decision
SI → Trust	0.298	0.054	5.519	0.000	—
PR → Trust	−0.438	0.059	−7.424	0.000	—
PE → AI Adoption	0.391	0.061	6.410	0.000	H1a Supported
EE → AI Adoption	0.287	0.059	4.864	0.000	H1b Supported
SI → AI Adoption	0.234	0.057	4.105	0.000	H1c Supported
PR → AI Adoption	−0.312	0.054	−5.778	0.000	H3 Supported
Trust → AI Adoption	0.489	0.062	7.887	0.000	—
R^2 (Trust)	0.481				
R^2 (AI Adoption)	0.567				

7.5 Mediation Analysis

Table 6 *Mediation of Trust in UTAUT2–AI Adoption Relationships*

Path	Direct Effect	Indirect via Trust	Total	Mediation Type
PE → AI	0.391 (0.312*)	0.201 [0.134, 0.278]**	0.513	Partial
EE → AI	0.287 (0.241*)	0.169 [0.107, 0.241]**	0.410	Partial
SI → AI	0.234 (0.186*)	0.146 [0.089, 0.214]**	0.332	Partial
PR → AI	−0.312 (−0.214*)	−0.187 [−0.258, −0.121]**	−0.401	Partial

Note. Values in parentheses = direct effect when trust included. Bootstrapped 95% CIs reported. * p < 0.05; ** 95% CI excludes zero. H2a–c and H4 all supported.

7.6 Multi-Group Analysis Results

Table 7 *Standardized Path Coefficients by Country Group*

Path	Nigeria (n=156)	Mexico (n=157)	India (n=155)	Sig. Difference?
PE → AI Adoption	0.312*	0.387**	0.489***	Yes (India > Nigeria)†
EE → AI Adoption	0.253*	0.421***	0.241*	Yes (Mexico > Nigeria, India)†
SI → AI Adoption	0.398***	0.198*	0.219*	Yes (Nigeria > Mexico, India)†
PR → AI Adoption	−0.287**	−0.378***	−0.271**	Yes (Mexico > Nigeria,

Path	Nigeria (n=156)	Mexico (n=157)	India (n=155)	Sig. Difference?
				India)†
Trust → AI Adoption	0.501***	0.461***	0.512***	No

Note. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. †χ^2 difference tests significant at $p < 0.05$ for pairwise comparisons. **H5 Supported.**

8. Discussion

The full-sample findings confirm UTAUT2's explanatory power in AI financial service adoption contexts, with $R^2 = 0.567$ for adoption intention substantially exceeding typical TAM applications ($R^2 \approx 0.35–0.45$). Trust's central mediating role confirms that positive technology perceptions translate into adoption intention primarily through the building of relational confidence in AI systems—a finding with profound implications for platform design and consumer communication strategy. Perceived risk's significant negative effect ($\beta = -0.312$) underscores that algorithmic opacity, data privacy concerns, and financial loss risk remain formidable barriers even in technologically progressive consumer segments.

The multi-group findings are theoretically and practically significant. Performance expectancy's dominance in India aligns with the utilitarian orientation of India's digital financial service adoption literature (NPCI, 2023). Social influence's primacy in Nigeria resonates with collectivist cultural norms and word-of-mouth dynamics in informal financial networks. Mexico's effort expectancy emphasis reflects uncertainty avoidance tendencies (Hofstede, 2011) and usability concerns among consumers with heterogeneous digital literacy levels.

9. Theoretical Implications

This study extends UTAUT2 in three directions. First, it operationalizes consumer trust and perceived risk as joint mediators within the UTAUT2 framework, augmenting the model's psychological depth for AI adoption contexts. Second, multi-group analysis reveals that UTAUT2 is not culturally invariant: the relative importance of constructs varies meaningfully across national contexts, supporting the theoretical integration of Hofstedean cultural dimensions as boundary conditions. Third, the trust-as-risk-mitigator pathway provides empirical grounding for Pavlou's (2003) theoretical model in AI financial service environments.

10. Practical Implications

Fintech firms targeting Nigerian markets should invest in social proof mechanisms—peer testimonials, community influencer endorsements, and tribal leader partnerships—that activate social influence pathways. Mexican market strategies should prioritize interface simplicity, multilingual support, and step-by-step onboarding that reduces effort expectancy barriers. Indian fintech platforms should foreground performance

evidence—ROI calculators, comparative return data, and transparent algorithmic recommendations—that activate performance expectancy. Across all markets, trust-building through regulatory certification, cybersecurity communication, and transparent AI explainability represents the highest-leverage investment for AI adoption acceleration.

11. Conclusion

This study examined AI adoption intention in financial services across 468 consumers in Nigeria, Mexico, and India using CB-SEM and multi-group analysis. Grounded in UTAUT2, findings confirm that performance expectancy, effort expectancy, and social influence predict adoption intention, mediated by consumer trust. Perceived risk negatively predicts adoption, partially mitigated by trust. Multi-group analysis reveals significant cross-country heterogeneity with actionable strategic implications. Future research should employ longitudinal designs to capture adoption behavior—not merely intention—and extend analysis to rural and financially excluded populations.

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