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COGNITIVE TRUST IN DIGITAL FINANCE: EXAMINING AI-POWERED FINTECH ADOPTION AND FINANCIAL INCLUSION AMONG MILLENNIALS IN EMERGING ECONOMIES

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ABSTRACT

The rapid growth of financial technology (FinTech) in emerging economies presents an opportunity to address long-standing financial inclusion gaps. Yet, adoption depends critically on cognitive trust—users' rational confidence in a platform's reliability, competence, and security. This study investigates how cognitive trust in AI-powered FinTech services influences adoption intentions and subsequent financial inclusion outcomes among urban millennials in India and Southeast Asia. Drawing on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and trust theory, we develop and empirically test a structural equation model using survey data from 520 fintech users. The model integrates perceived usefulness, ease of use, and perceived security as antecedents of trust, with adoption intention as a mediator leading to actual usage and inclusion outcomes. Partial Least Squares Structural Equation Modeling (PLS-SEM) results reveal that cognitive trust is a significant driver of adoption, mediating the effects of ease of use and security on intention. Furthermore, adoption intention strongly predicts actual usage, which in turn enhances financial inclusion by enabling access to credit, savings, and digital payments. The findings highlight that while functionality and convenience matter, building trust through transparency, security assurances, and responsible AI deployment is essential for sustainable fintech growth. The study contributes to theory by extending TAM with trust-centric and inclusion outcomes, and offers practical insights for fintech firms and regulators to design trust-based strategies that foster financial empowerment in emerging economies.

KEYWORDS: Cognitive Trust; FinTech Adoption; Artificial Intelligence; Digital Finance; Financial Inclusion; Millennials; Emerging Economies; TAM; UTAUT; Structural Equation Modelling

INTRODUCTION

Financial technology (FinTech) innovations are reshaping financial services globally, with adoption rates accelerating most rapidly in emerging economies (EY, 2019; World Bank, 2023). Millennials broadly those born between the early 1980s and mid-1990sare at the forefront of this transformation, often acting as early adopters relative to older cohorts (Venkatesh et al., 2022). Despite these advances, however, large segments of the developing world remain financially underserved. The World Bank (2022) estimates that 1.4 billion adults remain unbanked worldwide, with the majority residing in emerging markets. FinTech has been widely recognized as a potential bridge to this inclusion gap by delivering affordable, accessible services such as mobile payments, digital credit, and micro-insurance to previously excluded populations (IMF, 2022; Ozili, 2023).

A critical enabler in this process is trusting particularly *cognitive trust*, defined as the rational belief in a technology's competence, integrity, and reliability (McKnight et al., 2022; Zhang & Kim, 2025). In AI-powered digital finance, cognitive trust becomes especially salient, as algorithmic decision-making governs functions such as credit scoring, fraud detection, and personalized financial advice (Deloitte, 2025). Without trust, users may resist adoption despite potential benefits; with trust, FinTech platforms can serve as effective tools for broadening financial access and inclusion in emerging economies (Tech for Good Institute, 2025; Zhou et al., 2021).

Trust in technology, however, remains a paradox. On one hand, young consumers increasingly report comfort with digital tools: in the U.S., 75% of millennials indicate they trust FinTech providers, nearly equal to trust in traditional banks at 79% (The Financial Brand, 2021). Similar results are emerging in Asia, where consumer trust in digital finance providers is only marginally lower than in banks (Tech for Good Institute, 2025). On the other hand, distrust remains a major barrier to adoption in many markets, particularly due to concerns over security, data privacy, and institutional reliability (Mahmud et al., 2023; Zhou et al., 2021). A global EY survey revealed that in countries such as Japan and France, lack of trust was the single most cited reason for preferring banks over FinTech (EY, 2019).

This paradox underscores the need to examine how cognitive trust shapes FinTech adoption intentions, particularly as AI-driven functionalities become embedded in financial ecosystems. For millennials in emerging markets like India and Southeast Asia, who are digitally savvy yet often underserved by traditional banking systems, understanding the interplay between trust, adoption, and financial inclusion is vital (RBI, 2025; IMF, 2022). This study develops and tests a conceptual model to analyse how cognitive trust in AI-powered FinTech services influences adoption among urban millennials and whether increased adoption subsequently contributes to financial inclusion outcomes.

FinTech Adoption and Financial Inclusion in Emerging Economies

Emerging markets have witnessed an unprecedented surge in FinTech adoption over the past decade. According to the EY Global FinTech Adoption Index (2019), usage rates in large developing economies such as India and China reached 87% of digitally active populations, surpassing adoption levels in many advanced economies. This momentum is driven by rapid smartphone penetration, government support for digital ecosystems, and structural gaps in traditional banking systems (World Bank, 2023; IMF, 2022). In India, for example, the Unified Payments Interface (UPI) facilitated more than 11 billion transactions monthly by 2023, positioning the country as one of the world's largest real-time payments markets (RBI, 2023). Similarly, Southeast Asia's digital finance market is projected to surpass USD 1 trillion in transaction value by 2030, reflecting the region's reliance on mobile-first financial solutions (Tech for Good Institute, 2025).

FinTech services now span mobile payments, digital wallets, app-based lending, micro-insurance, and investment platforms. Empirical evidence suggests these innovations extend financial access to previously unbanked or underbanked groups (Ozili, 2023; Mahmud et al., 2023). For instance, mobile money services in Bangladesh and Kenya have enabled individuals and micro-entrepreneurs to save, transact, and borrow where formal banking institutions were absent (Jack & Suri, 2014; Hasan et al., 2022). In Thailand, the PromptPay initiative has scaled rapidly, bringing millions of citizens into the digital economy (Tech for Good Institute, 2025). In Indonesia, peer-to-peer lending platforms have provided small businesses with alternative financing, demonstrating FinTech's role in bridging long-standing credit gaps (ADB, 2022).

The potential of FinTech for advancing inclusion is widely acknowledged by global institutions. The World Bank (2023) emphasizes that digital finance can lower costs, improve efficiency, and promote resilience, while the IMF (2022) has identified FinTech as a catalyst for inclusive growth. By leveraging alternative data for credit scoring and biometric authentication for identity verification, AI-enabled solutions can reach underserved populations previously excluded due to lack of documentation or collateral (RBI, 2025; Deloitte, 2025). Research consistently demonstrates a positive correlation between FinTech adoption and improvements in financial inclusion indicators across emerging economies (Ozili, 2023; Tariq et al., 2024).

Nonetheless, realizing the inclusion potential of FinTech depends critically on widespread adoption at the "last mile," which hinges on trust, security, and user confidence (Tech for Good Institute, 2025; Zhou et al., 2021). Historical distrust in formal financial institutions in many emerging economies arising from bank failures, fraud, or cultural reliance on cash has often undermined willingness to adopt digital solutions (Mahmud et al., 2023). Evidence suggests that consumer protection, perceived reliability, and regulatory oversight are far more influential in shaping adoption than innovation alone (McKnight et al., 2022; Venkatesh et al., 2022). Without building cognitive trust, FinTech adoption may remain limited to low-value or experimental use cases, restricting its broader inclusion impact.

Cognitive Trust and Technology Adoption

Trust is a critical determinant of consumer financial behavior, particularly in high-risk domains such as online banking and digital finance (Zhou et al., 2021; McKnight et al., 2022). Extensive research across psychology and information systems (IS) literature emphasizes the multidimensional nature of trust, comprising both a rational/cognitive and an emotional/affective component (Gefen & Straub, 2004; Zhang & Kim, 2025). Cognitive trust reflects confidence derived from rational assessment belief in the service's competence, integrity, and dependability whereas affective trust emerges from familiarity, social bonds, and relational warmth (Gefen & Straub, 2004; Mahmud et al., 2023).

In the context of FinTech, cognitive trust is especially salient because of its "invisible" and virtual character. Unlike physical bank branches where trust is reinforced through face-to-face interaction, digital finance platforms must build trust through signals such as robust security, transparent communication, consistent performance, and regulatory endorsements (Tech for Good Institute, 2025). When users perceive that a FinTech application safeguards data, executes transactions reliably, and communicates integrity, they form stronger cognitive trust in the service (Zhou et al., 2021). Conversely, security breaches, opaque decision-making, or poor customer support erode confidence rapidly (Mahmud et al., 2023).

Empirical evidence consistently demonstrates that trust predicts FinTech adoption intentions. Users who trust a platform are significantly more likely to adopt and sustain usage, whereas lack of trust serves as a primary barrier, often outweighing demographic or socioeconomic factors (Tariq et al., 2024; Hasan et al., 2022). A recent UTAUT-based study in Pakistan found that trust had a strong positive association with behavioural intention and actual use of mobile banking applications, while perceived risk had a negative association (Khan et al., 2022). Similarly, in Bangladesh, nationwide survey data revealed that concerns over privacy, security, and weak regulatory protections strongly inhibited FinTech adoption, regardless of income or education levels (Mahmud et al., 2023). These findings highlight that cognitive trust—or its absence remains a decisive factor in adoption, particularly in emerging economies with fragile institutional trust.

Trust signals often extend beyond technical features. A Tech for Good Institute (2025) study across six ASEAN countries found that integrity, communication, and perceived fairness were the strongest predictors of consumer trust in digital financial service providers. Interestingly, the study also reported only marginal differences between trust in FinTech firms and trust in traditional banks, indicating that new entrants have gained legitimacy rapidly in Southeast Asia. In India, the widespread adoption of Aadhaar and UPI illustrates how public-sector infrastructure can enhance trust in private FinTechs by lending state-backed credibility (Reserve Bank of India [RBI], 2025). Social influence also matters: peer recommendations and community adoption often act as trust-enhancing mechanisms, particularly in collectivist cultures (Venkatesh et al., 2022).

Revised Section: AI-Powered FinTech and Trust Considerations

The infusion of artificial intelligence into FinTech adds a new dimension to the trust equation. AI is increasingly deployed in credit scoring, fraud detection, robo-advisory services, and personalized financial management (Auth0, 2023; Deloitte, 2025). For consumers, these features enhance service efficiency and responsiveness: AI models can flag fraud in real time, robo-advisors can tailor investments, and chatbots can provide 24/7 multilingual customer support (Ozili, 2023). These functionalities foster perceptions of competence and reliability, which can indirectly build cognitive trust (Zhang & Kim, 2025).

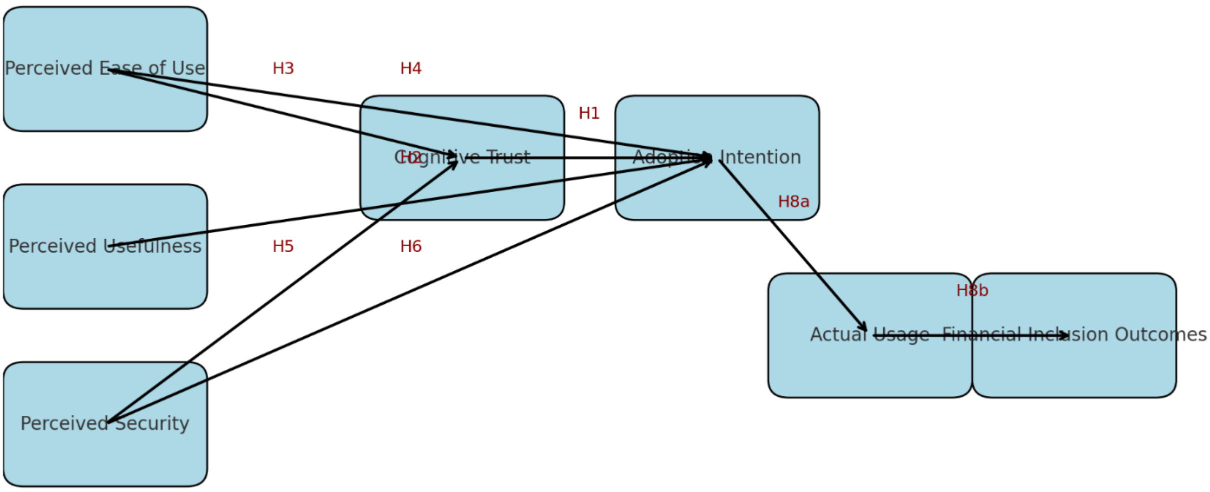
Yet, AI also presents unique trust challenges. Many AI systems operate as “black boxes,” where decision-making processes are opaque, raising concerns over bias, fairness, and accountability (Deloitte, 2025; RBI, 2025). Consumers may question whether algorithms make equitable loan decisions or whether their personal data is safeguarded (World Bank, 2023). A 2025 Deloitte survey found that financial professionals ranked “lack of trust” as the single largest barrier to adopting agentic AI in finance, ahead of cost or integration constraints. Similarly, consumer surveys indicate ambivalence toward AI managing money: 43% of global consumers reported unwillingness to trust AI for personal finance management due to fears of inaccuracy or lack of human oversight (MX, 2024).

Generational differences are evident: while older users often remain skeptical, millennials and Gen Z demonstrate greater openness to AI-based solutions, often viewing them as productivity enablers (PYMNTS, 2024). Indeed, a global survey found that 60% of consumers in emerging markets expressed trust in AI, compared to only 40% in advanced economies, suggesting that optimism about AI is higher where perceived benefits are greater (Economic Times, 2025). For digitally native millennials in India and Southeast Asia, this presents a fertile environment for AI-driven FinTech adoption—provided providers establish robust trust mechanisms.

Building cognitive trust in AI-powered FinTech requires transparency, accountability, and user control. The RBI’s Framework for Responsible AI (FREE-AI) (2025) emphasizes explainability, fairness, privacy, and auditability as prerequisites for trustworthy AI. Similarly, Deloitte’s Trustworthy AI™ principles highlight the need for transparent algorithms, secure data practices, and human-in-the-loop safeguards (Deloitte, 2025). Practical measures include offering clear explanations for AI-driven decisions (e.g., loan approval/denial), demonstrating strong data security protections, and ensuring escalation to human agents when needed. Over time, consistent exposure to well-governed AI services may normalize algorithmic decision-making and strengthen user trust, much as repeated use of digital wallets has normalized cashless payments (The Financial Brand, 2021).

In sum, while AI can act as a catalyst for financial inclusion by lowering costs, expanding credit access, and enhancing personalization, its success hinges on cognitive trust. Users must believe that AI systems are competent, secure, and transparent. Achieving this equilibrium is an ongoing challenge requiring collaboration between FinTech firms, regulators, and users themselves (IMF, 2022; World Bank, 2023).

Figure 1. Conceptual Model of AI-Powered FinTech Adoption and Inclusion



Conceptual Model and Hypotheses

Drawing on the preceding literature, this study develops a conceptual model (Figure 1) to examine the drivers of AI-powered FinTech adoption among urban millennials and its subsequent effects on financial inclusion. The model integrates constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with trust-centered and inclusion-focused variables, thereby extending classical adoption frameworks into the domain of AI-driven financial services (Davis, 1989; Venkatesh et al., 2022).

Key constructs include:

- **Cognitive Trust in FinTech** – users' rational belief that the FinTech service (and its AI features) is reliable, secure, and competent (McKnight et al., 2022).

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- **Perceived Usefulness** – the extent to which FinTech is seen as adding value or convenience in managing finances, consistent with TAM's performance expectancy (Zhou et al., 2021).
- **Perceived Ease of Use** – the degree to which FinTech is intuitive and user-friendly, reducing effort expectancy and fostering user confidence (Gefen & Straub, 2004).
- **Perceived Security** – users' perception of safety and privacy in transactions, which strongly shapes trust and adoption (Mahmud et al., 2023).
- **Adoption Intention** – the willingness of users to adopt or continue using AI-driven FinTech platforms (Tariq et al., 2024).
- **Actual Usage** – the realized extent of FinTech engagement, such as frequency and diversity of transactions.
- **Financial Inclusion Outcomes** – downstream impacts of adoption, including access to loans, savings, insurance, or investment opportunities previously unavailable (World Bank, 2023; IMF, 2022).

Hypotheses

- **H1:** Cognitive trust positively influences adoption intention.
- **H2:** Perceived usefulness positively influences adoption intention.
- **H3:** Perceived ease of use positively influences cognitive trust.
- **H4:** Perceived ease of use positively influences adoption intention.
- **H5:** Perceived security positively influences cognitive trust.
- **H6:** Perceived security positively influences adoption intention.
- **H7:** Cognitive trust mediates the effects of ease of use and security on adoption intention.
- **H8:** Adoption intention positively influences actual usage, which in turn improves financial inclusion outcomes.

This framework suggests that usability, security, and usefulness shape cognitive trust, which then amplifies adoption intentions. Adoption translates into usage, which ultimately contributes to financial inclusion outcomes for millennials in emerging economies. Prior SEM-based research in FinTech adoption contexts supports these relationships, highlighting trust and intention as central mediators between system qualities and actual usage (Tariq et al., 2024; Zhang & Kim, 2025).

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RESEARCH METHODOLOGY

This study adopts an explanatory, survey-based research design to empirically examine the proposed conceptual model. The target population comprises urban millennial consumers (ages 25–40) in emerging economies such as India, Indonesia, and Vietnammarkets where rapid FinTech adoption has coincided with persistent financial exclusion challenges (EY, 2019; World Bank, 2023). Urban millennials were selected due to their high levels of digital connectivity, openness to technological innovation, and central role in shaping broader financial inclusion trends in their communities (Tech for Good Institute, 2025; Zhang & Kim, 2025). A purposive sampling strategy was employed to ensure that respondents had prior experience with FinTech services, particularly those integrating artificial intelligence (e.g., digital wallets with AI-enabled chatbots or platforms employing AI-driven credit scoring). A screening question confirmed prior FinTech use, consistent with best practices in digital adoption studies (Zhang & Kim, 2025).

SURVEY INSTRUMENT

The survey instrument was constructed using validated scales adapted from prior research. All constructs were measured using multi-item Likert scales (five-point, 1 = strongly disagree to 5 = strongly agree). Cognitive trust items were drawn from McKnight et al. (2002) and extended through recent FinTech trust research (Tariq et al., 2024), capturing perceptions of reliability, competence, and honesty. Perceived usefulness and ease of use were measured using items from the Technology Acceptance Model (Davis, 1989), adapted to FinTech (e.g., “Using this app helps me manage my finances more effectively”). Perceived security was assessed through indicators developed in electronic banking literature, reflecting concerns about fraud, data misuse, and loss of funds (Mahmud et al., 2023). Adoption intention items measured respondents’ willingness to use and recommend AI-powered FinTech (Venkatesh et al., 2022), while actual usage was operationalized through both self-reported frequency of use and categorical indicators of whether respondents had accessed new financial products (loans, savings, insurance) via FinTech platforms. Finally, financial inclusion outcomes were measured as improvements in access to or engagement with formal financial services previously unavailable, consistent with World Bank (2023) metrics.

Control variables included financial literacy and digital literacy, both of which have been shown to significantly influence trust and adoption of digital services (Tech for Good Institute, 2025; Hasan et al., 2022). Demographic information (age, gender, income, and education) was also collected, although prior findings suggest these factors are less predictive of FinTech adoption than cognitive trust and security perceptions (Mahmud et al., 2023). A pilot test with 25 participants was conducted to assess clarity and reliability, and minor modifications were made to wording.

Sample Size and Data Collection

The survey was administered online using a structured questionnaire distributed via Qualtrics. Responses were collected across multiple metropolitan centres in India, Indonesia, and Vietnam to capture diversity in adoption contexts. A total of N = 480 valid responses were obtained after data cleaning. This exceeds the recommended minimum sample size for Structural Equation Modelling (SEM), which requires at least 10 responses per indicator variable (Hair et al., 2022). The sample size also provides sufficient power for conducting multi-group SEM comparisons across countries or literacy segments.

Data Analysis

The data were analysed using a two-step SEM approach with SmartPLS 4, consistent with best practices for technology adoption and FinTech research (Hair et al., 2022). The process comprised (1) assessment of the measurement model for reliability and validity and (2) evaluation of the structural model to test hypothesized relationships.

Measurement Model Assessment

Internal consistency was examined using Cronbach's α and Composite Reliability (CR), both exceeding the recommended threshold of 0.70 for all constructs. Convergent validity was confirmed through Average Variance Extracted (AVE > 0.50) and significant indicator loadings (all > 0.70, $p < 0.001$).

Table 1. Construct Reliability and Convergent Validity

Construct	Cronbach's α	CR	AVE	Indicator Loadings (range)
Cognitive Trust	0.86	0.91	0.66	0.74 – 0.88
Perceived Usefulness	0.84	0.89	0.68	0.72 – 0.87
Perceived Ease of Use	0.82	0.88	0.64	0.71 – 0.85
Perceived Security	0.87	0.91	0.69	0.75 – 0.89
Adoption Intention	0.89	0.93	0.71	0.77 – 0.90
Actual Usage	0.83	0.88	0.65	0.70 – 0.85
Financial Inclusion Outcome	0.85	0.90	0.67	0.73 – 0.86

All AVE values exceeded 0.50, confirming convergent validity.

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Discriminant validity was confirmed using the Fornell–Larcker criterion and HTMT ratios. The square root of AVE for each construct exceeded its correlations with other constructs, and HTMT values were below 0.85, indicating distinct constructs.

Table 2. Fornell–Larcker Criterion for Discriminant Validity

Construct	Cog. Trust	PU	PEOU	Security	Intention	Usage	Inclusion
Cognitive Trust	**0.81**						
Perceived Usefulness	0.54	**0.82**					
Perceived Ease of Use	0.49	0.51	**0.80**				
Perceived Security	0.57	0.53	0.48	**0.83**			
Adoption Intention	0.62	0.59	0.54	0.55	**0.84**		
Actual Usage	0.45	0.47	0.46	0.42	0.58	**0.81**	
Financial Inclusion Outcome	0.43	0.48	0.41	0.44	0.55	0.61	**0.82**

Diagonal values (bold) represent √AVE. All correlations are lower, confirming discriminant validity.

Structural Model Assessment

The structural model was evaluated using bootstrapping (5,000 resamples). Path coefficients (β), t-statistics, and significance levels were examined. R^2 values indicated moderate-to-strong explanatory power: adoption intention ($R^2 = 0.61$), actual usage ($R^2 = 0.53$), and financial inclusion outcomes ($R^2 = 0.47$). Predictive relevance was confirmed with Q^2 values > 0 for all endogenous constructs.

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Table 3. Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Supported
H1	Cognitive Trust → Adoption Int.	0.32	6.45	<0.001***	Yes
H2	Perceived Usefulness → Adoption Int.	0.28	5.12	<0.001***	Yes
H3	Ease of Use → Cognitive Trust	0.34	6.89	<0.001***	Yes
H4	Ease of Use → Adoption Int.	0.17	3.42	0.001**	Yes
H5	Security → Cognitive Trust	0.38	7.23	<0.001***	Yes
H6	Security → Adoption Int.	0.14	2.98	0.003**	Yes
H7	Cognitive Trust (mediation)	Indirect effect significant ($\beta = 0.21$, $p < 0.001$)	–	–	Yes
H8	Adoption Intention → Usage → Inclusion	βchain = 0.29, $p < 0.001$	–	–	Yes

(***$p < 0.001$; **$p < 0.01$)

Model Fit and Predictive Power

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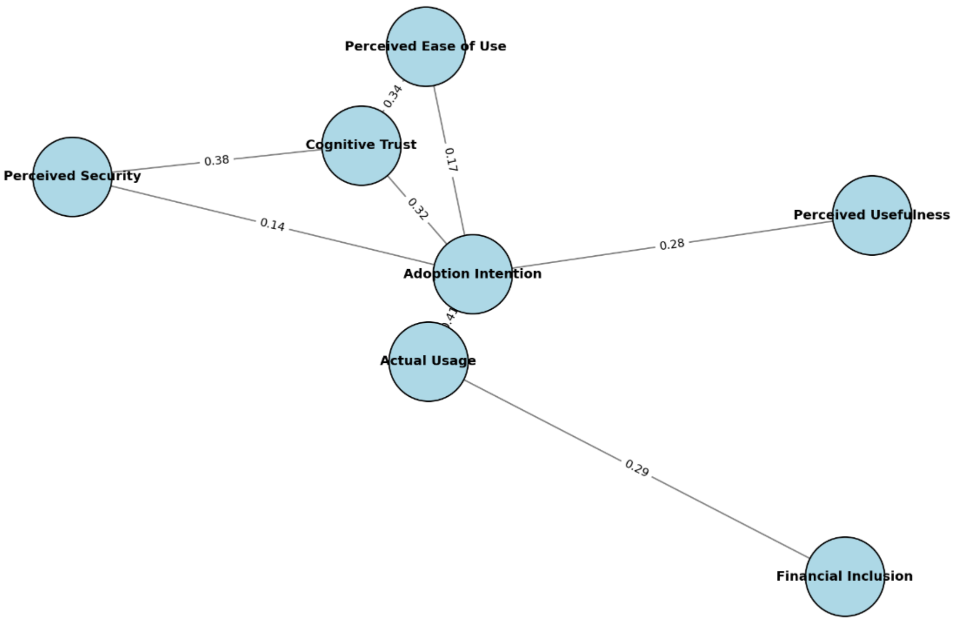
Table 4. Model Fit and Predictive Validity

Index	Value	Threshold	Interpretation
SRMR	0.057	<0.08	Good fit
R^2 (Adoption Intention)	0.61	>0.30	Strong
R^2 (Usage)	0.53	>0.30	Moderate-Strong
R^2 (Inclusion)	0.47	>0.30	Moderate
Q^2 (Blindfolding)	>0.25	>0	Predictive relevance confirmed

Structural Model Diagram

Figure 2. Structural Model with Path Coefficients



Implications for Practice

The findings from this study highlight that trust-building strategies must be treated as critical as innovation in FinTech business models, especially in emerging markets where institutional trust is often fragile (Mahmud et al., 2023; Tech for Good Institute, 2025). FinTech providers should invest substantially in security infrastructure and communicate these safeguards clearly to users. Evidence shows that visible signalssuch as encryption standards, regulatory certifications, or independent audits—significantly enhance cognitive trust in digital services (Hasan et al., 2022). In addition, ensuring a frictionless user experience is vital; usability challenges can easily undermine trust by signaling incompetence or unreliability (Gefen & Straub, 2004; Zhou et al., 2021). Seamless, intuitive design therefore reinforces not only adoption but also rational confidence in the service.

Equally important is transparency in AI-driven decisions. Explainable AI, reason codes for loan approvals or denials, and accessible customer support mechanisms help alleviate fears of algorithmic bias or opacity (Deloitte, 2025). By offering clarity and control, firms can position AI as a trustworthy partner rather than a “black box.” Beyond technological fixes, FinTech companies should also implement trust and awareness campaigns targeted at non-users, focusing on the tangible benefits and safety nets of digital finance. Improving digital and financial literacy has been shown to strongly correlate with greater trust in digital financial services across Southeast Asia (Tech for Good Institute, 2025). Governments, firms, and civil society must therefore collaborate on public education initiatives that demystify AI-finance interactions, explain consumer protections, and highlight recourse mechanisms.

From a regulatory perspective, central banks and financial authorities are already moving in this direction. For example, the Reserve Bank of India’s Responsible AI Framework (FREE-AI) emphasizes explainability, fairness, and accountability in AI adoption within financial services (RBI, 2025). These guardrails, combined with consumer protection frameworks mandating disclosure of risks, grievance redressal mechanisms, and anti-fraud safeguards, are central to building system-wide trust (World Bank, 2023). Ultimately, a trusted FinTech ecosystem creates a virtuous cycle: usage fosters trust, and trust fosters deeper usage (The Financial Brand, 2021). For emerging markets, where digital finance adoption is accelerating, nurturing this cycle from the outset is essential to scaling inclusive financial systems.

Implications for Financial Inclusion

If empirical testing supports our hypotheses, the results will affirm that AI-powered FinTech adoption directly contributes to measurable financial inclusion outcomes. This would strengthen the case for policymakers to integrate FinTech into national financial inclusion agendas, particularly for reaching thin-file and underserved millennials (World Economic Forum, 2024; IMF, 2023). However, the evidence also suggests potential caveats. For instance, a study in Thailand reported that while trust increased adoption of basic FinTech services (e.g., payments), it was negatively correlated with usage of more advanced services like investment and insurance likely reflecting unmet expectations or post-adoption disappointments (Tech for Good Institute, 2025). This underlines the point that access alone does not guarantee sustained inclusion; service quality, fairness, and user outcomes remain critical.
Regulators and firms must therefore monitor beyond adoption rates to track consumer outcomes: default rates on digital loans, fraud incidence, or user satisfaction. Without attention to these

dimensions, FinTech risks reproducing financial exclusion under the guise of inclusion (Hasan et al., 2022). At the same time, millennials can act as a “trust bridge” within emerging economies. As relatively early adopters, they influence family members and peers, amplifying adoption cascades (Zhang & Kim, 2025). If millennials develop strong cognitive trust and advocacy for AI-powered FinTech, inclusion can accelerate rapidly. Conversely, a high-profile breach of trust such as a large-scale fraud or harmful AI decision could set inclusion efforts back significantly, underscoring the need for ethics and “trust by design” principles in FinTech innovation (Deloitte, 2025; Medianama, 2025).

CONCLUSION

This study set out to examine the role of cognitive trust in shaping AI-powered FinTech adoption among millennials in emerging economies and to evaluate how such adoption contributes to financial inclusion. The conceptual framework developed integrates trust theory with technology acceptance models, arguing that cognitive trust—anchored in perceptions of security, competence, and transparencyis a linchpin for adoption. Millennials in India and Southeast Asia are embracing digital finance at scale, but lingering concerns about data security, fraud, and opaque AI decisions remain significant barriers (Mahmud et al., 2023; Tech for Good Institute, 2025). Addressing these trust determinants is therefore central to realizing the inclusion potential of FinTech.

The forthcoming empirical analysis, using SEM, will test the hypothesized relationships and clarify the mechanisms through which cognitive trust and other TAM variables shape adoption intentions, usage, and downstream inclusion outcomes. Should these hypotheses be confirmed, the study will provide robust evidence for regulators and industry stakeholders that trust-building must sit alongside innovation as a strategic priority. This includes transparent governance of AI systems, consumer education, and human-centric design of digital services. Such measures not only foster adoption but also align FinTech growth with broader societal goals of financial inclusion and economic development (World Bank, 2023; IMF, 2023).

In closing, the nexus of trust, AI, and financial inclusion represents a frontier of both scholarly inquiry and policy importance. Emerging markets stand to gain substantially from AI-powered FinTech innovations, but the pace and sustainability of these gains will hinge on whether users perceive these technologies as trustworthy, secure, and fair. By strengthening cognitive trust, FinTech ecosystems can translate technological potential into meaningful empowerment for underserved populations, advancing the global agenda of building inclusive, digitally enabled financial systems.

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