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Continuance Intention Towards AI-Enabled Fintech Services in India: Examining the Roles of Trust and Perceived Privacy Risk Method

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Abstract

With India's rapid digital transformation driven by the Unified Payments Interface ecosystem and widespread adoption of AI-powered fintech services, such as Google Pay, PhonePe, and Paytm, understanding the determinants of users' continuance intention has become increasingly critical. Despite extensive research on fintech adoption, post-adoption behavior and continuance usage of AI-enabled fintech services in emerging economies like India remain underexplored. This study addresses this gap by developing and validating a comprehensive model integrating parasocial relationship theory, trust-commitment theory, UTAUT2, and the Service Robot Acceptance Model (sRAM). Survey data from 624 fintech AI users across Karnataka, India, provide rich insights into AI-enabled fintech service continuance in a rapidly digitizing economy. The findings reveal that performance expectancy, hedonic motivation, and social influence positively impact engagement and continuance intentions, with perceived intelligence and perceived accuracy also playing significant roles. The study establishes the moderating effect of perceived privacy risk on several key relationships, advancing the understanding of AI-enabled fintech service continuance in the Indian context.

Keywords: Fintech; UTAUT2; Trust-commitment Theory; Parasocial Relationship Theory; Perceived Privacy Risk; and UPI Ecosystem

1. Introduction

Artificial intelligence (AI) is fundamentally reshaping the financial services landscape in India, particularly through the proliferation of AI-enabled fintech applications such as Google Pay, PhonePe, and Paytm (Gupta et al., 2021) . These platforms leverage intelligent automation, conversational agents, and predictive algorithms to streamline payments, offer personalized financial recommendations, and enhance customer engagement on an unprecedented scale (Kesavan & Srinivasan, 2025) . India's Unified Payments Interface (UPI) processed over 100 billion transactions in 2023 alone, reflecting the massive and growing dependence of Indian consumers on AI-driven fintech services (Tomer, 2024) .

Businesses operating within India's digital economy increasingly leverage AI to reduce transaction friction, personalize user experiences, and drive financial inclusion across diverse socioeconomic groups. Consumer preferences are rapidly shifting toward AI-driven fintech services, attracted by their real-time responsiveness, convenience, and increasingly human-like interaction capabilities (Mehta et al., 2025) . The impact of AI on daily financial life is evident through widely adopted applications such as PhonePe's AI-powered fraud detection, Google pays intelligent transaction suggestions, and Paytm's conversational customer support chatbot, which collectively shape millions of daily consumer interactions across Karnataka and the broader Indian market (Bansal, 2025; Sonia, 2025) .

In homes and on mobile devices, AI-enabled fintech services, including intelligent virtual assistants embedded within payment applications, are revolutionizing human–technology interactions through anthropomorphic and socially intelligent features (Hajare, 2025; Mori, 2021) . These agents facilitate a wide range of tasks, including peer-to-peer fund transfers, bill payments, investment advisory, and credit scoring. With over 750 million smartphone users and a rapidly expanding digital-native population, India represents one of the world's most significant markets for AI-enabled fintech adoption (Gupta et al., 2021) .

Despite the rapid growth of AI-enabled fintech services, research on their continued usage remains limited, particularly regarding trust and user behavior in the Indian context (Patil, 2024) . The rising popularity of AI-powered fintech applications has led to increased concerns about cyber fraud

and data misuse, raising significant consumer anxieties regarding the privacy and security of their financial information (Srivastava & Dhamija, 2022). These concerns are particularly salient in Karnataka, a technology hub hosting numerous fintech startups and a digitally literate user base, where the tension between AI adoption and privacy protection is strongly felt. India's newly enacted Digital Personal Data Protection (DPDP) Act of 2023 further underscores the national importance of data privacy in digital financial services (Kaur, 2024; Pasupuleti, 2024) .

Despite the growing body of research on AI-enabled services globally, prior studies have not fully explored the unique dynamics of AI-enabled fintech service continuance in India (B et al., 2022) . This study addresses this gap by developing an integrated framework that examines how the social, cognitive, and emotional dimensions of AI fintech services influence users' continuance intentions in Karnataka. Using partial least squares structural equation modeling and data from 624 AI fintech users across Karnataka, this study provides actionable insights into the factors influencing AI-enabled fintech service continuance in one of the world's fastest-growing digital economies (Tiwari et al., 2024) .

Our contributions are fourfold: (1) we offer a comprehensive understanding of the factors driving continued AI fintech service use in India, extending beyond UTAUT2 and sRAM (Papathomas et al., 2025) ; (2) we examine AI-related social interaction variables, such as perceived social presence, anthropomorphism, and intelligence, as they manifest in fintech service environments (Manser Payne & O'Brien, 2024) ; (3) we analyze the moderating role of perceived privacy risk and the mediating effects of engagement and trust, which have largely been overlooked in Indian fintech literature (Venkaiah Babu & Mohideen, 2024) ; and (4) we provide a unique emerging economy perspective by focusing on Karnataka, in contrast to the Western-centric emphasis of most existing AI service studies (Varalakshmi, 2024) .

2. Theoretical Background and Hypotheses Development

The UTAUT2 (Venkatesh, 2021) is a widely adopted framework for technology acceptance in consumer settings. By synthesizing constructs from multiple theories, UTAUT2 emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of behavioral intention and technology use (Yuliani et al., 2024) . UTAUT2 provides a solid theoretical foundation for exploring AI-enabled fintech service acceptance, especially as these services incorporate sophisticated conversational AI and predictive capabilities that demand both rational and emotional considerations from users (Papathomas et al., 2025; Singh & Kumar, 2024) .

To provide a more holistic view, we incorporated trust-commitment theory, parasocial interaction theory, and sRAM alongside UTAUT2. Trust-commitment theory, introduced by (Morgan & Hunt, 1994) , is fundamental to understanding relationship dynamics in uncertain digital financial service environments. Trust is defined as a belief in the reliability and integrity of the service provider, while commitment reflects a long-term intention to maintain the relationship (Isaeva et al., 2020) . Parasocial interaction theory, originally proposed by (Horton & Richard Wohl, 1956) , describes the one-sided relationships individuals form with media figures extended to AI fintech agents. Users of platforms such as Paytm's AI assistant may develop parasocial bonds with these systems, influencing their financial behavior and willingness to share sensitive personal data (Kishor et al., 2024) . The sRAM extends the traditional technology acceptance model by incorporating functional, social-emotional, and relational dimensions relevant to human-AI interactions across sectors, including banking and retail, in India (A. Patil, 2024) .

2.1 Effort Expectancy

Effort expectancy refers to the degree to which users perceive AI-enabled fintech platforms such as Google Pay and PhonePe to be effortless and intuitive (Ramli et al., 2025) . While prior studies confirm the role of effort expectancy in technology engagement, its significance in the Indian fintech context must consider cognitive adaptation, as AI systems continuously evolve with new features, such as voice-based UPI payments and AI-driven credit assessments (Maity & Majumder, 2024; Shriya & Velmurugan, 2025) . Based on prior research demonstrating the influence of effort expectations on AI-enabled service acceptance, we propose the following hypothesis:

H1a. Effort expectancy positively impacts engagement with AI-enabled FinTech services.

H1b. Effort expectancy positively impacts the intention to use AI-enabled fintech services continuously.

2.2 Performance Expectancy

Performance expectancy captures users' beliefs that AI-powered fintech applications will help achieve greater efficiency, accuracy, and convenience in financial transactions(A & T, 2025; Pandey & Sergeeva, 2022) . As AI systems in fintech become increasingly sophisticated, incorporating real-time fraud alerts, predictive

spending insights, and automated investment recommendations, user expectations continuously evolve(Samonte & Navarro, 2024) . High-performance expectations create a reinforcing feedback cycle in which perceived service quality drives engagement, which in turn leads to continued usage.

H2a. Performance expectancy positively impacted engagement with AI-enabled fintech services in this study.

H2b. Performance expectancy positively impacted the continuous usage intention of AI-enabled fintech services.

2.3 Hedonic Motivation

Hedonic motivation encompasses the pleasure and intrinsic satisfaction derived from interacting with AI-enabled financial technology services (Williams, 2019) . In the Indian fintech context, gamification elements embedded in platforms such as PhonePe's scratch cards and Google Pay's reward challenges significantly enhance hedonic experiences, motivating users to engage more deeply and frequently (Mubashar & Sarwar, 2025) . The excitement and entertainment value of these hedonic attributes substantially influence Indian consumers interactions with and sustained use of AI-enabled fintech services (Saba et al., 2024; Tiwari et al., 2024) .

H3a. Hedonic motivation positively impacts engagement with AI-enabled FinTech services.

H3b. Hedonic motivation has a positive impact on the continuous usage intention of AI-enabled fintech services.

2.4 Social Influence

Social influence is particularly powerful in the Indian context, given the collectivist cultural orientation of Indian society (Verma, 2020) , where financial decisions are often shaped by family members, peers and community networks (Kim & Chawla, 2022) . When users observe that family members and peers in Karnataka actively use and endorse AI-enabled fintech platforms, they experience strong social pressure to adopt and continue using these services to align with the group norms (Tiwari et al., 2024) . Empirical evidence from Indian digital payment research consistently highlights social influence as central to driving adoption and sustained use (Gupta et al., 2021) .

H4a. Social influence positively impacted engagement with AI-enabled fintech services.

H4b. Social influence positively impacts the continuous usage intention of AI-enabled fintech services.

2.5 Perceived Social Presence and Trust

Perceived social presence refers to the extent to which users feel they are interacting with a socially aware and responsive AI entity rather than a mechanical system (Tiwari et al., 2024) . When AI agents on platforms such as Paytm exhibit conversational warmth and personalized responses, users develop heightened perceptions of social presence (Gokulanathan et al., 2025; Gupta et al., 2021) , which significantly increases their trust. This trust-building function of social presence is particularly critical in the Indian fintech context, where concerns about online financial fraud are prevalent (Poudel & Acharya, 2023; Saminathan & R, 2020) .

H5a. Perceived social presence positively impacts trust in AI-enabled fintech service.

H5b. Perceived social presence positively impacts the continuous usage intention of AI-enabled fintech services.

2.6 Perceived Anthropomorphism and Trust

Anthropomorphism involves users attributing human-like qualities, such as empathy, understanding, and communicative competence, to AI agents in payment and banking applications (Frazer, 2022; Uysal et al., 2023) . In the Indian context, where the quality of personal relationships is central to trust in financial services, anthropomorphic AI characteristics serve as powerful trust signals (Kasinathan et al., 2024) . When users perceive Google Pay's or PhonePe's AI assistant as exhibiting a human-like understanding of their financial needs, they develop higher levels of trust in these systems (Schreibelmayr et al., 2023) .

H6a. Perceived anthropomorphism positively impacts trust in AI-enabled FinTech services.

H6b. Perceived anthropomorphism positively impacts the intention to continuously use AI-enabled fintech services.

2.7 Perceived Intelligence and Trust

Perceived intelligence reflects users' beliefs that AI fintech systems can understand complex financial contexts, anticipate user needs, and provide contextually appropriate recommendations(Manikandan et al., 2024; Pereira et al., 2022) . Advanced AI capabilities in platforms such as Paytm's AI-driven credit scoring and PhonePe's predictive transaction suggestions enhance perceived intelligence, enabling more natural and contextually relevant interactions (S & M V, 2024) . The importance of perceived intelligence is amplified in the Indian fintech context, where users increasingly rely on AI-generated financial advice for decisions ranging from daily micro-payments to investment planning (Banupriya, 2026) .

H7a. Perceived intelligence positively impacts trust in AI-enabled FinTech services.
H7b. Perceived intelligence positively impacts the continuous usage intention of AI-enabled fintech services.

2.8 Perceived Accuracy and Continuance Intention

In the high-stakes domain of AI-enabled fintech services, perceived accuracy–the extent to which users believe that AI recommendations and information are reliable, unbiased, and contextually precise–is a critical determinant of continued usage (Schreibelmayr et al., 2023; Zhang, 2024) . Indian fintech users who rely on AI-generated transaction categorizations, spending analyses, and investment recommendations place enormous weight on accuracy because errors directly impact their financial wellbeing (Schreibelmayr et al., 2023; Thapa, 2024) .
H8. Perceived accuracy positively impacts the continuous usage intention of AI-enabled fintech services.

2.9 Personal Innovativeness and Continuance Intention

Personal innovativeness captures individuals' propensity to explore and adopt new technology-driven services (Bhagya Rathnayake, 2022) . In Karnataka's technology-forward environment, characterized by a high density of IT professionals and digital entrepreneurs, personal innovativeness is expected to play a significant role in driving continued engagement with AI-enabled fintech services (B. Kaur, 2024; Pasupuleti, 2024) . Individuals with high personal innovativeness are more likely to explore advanced features, such as Google Pay's AI investment advisor or Paytm's AI-powered insurance recommendations(Herrmann & Masawi, 2022; Jiang et al., 2022) .
H9. Personal innovativeness positively impacts the continuous usage intention of AI-enabled fintech services.

2.10 Trust and Continuance Intention

Trust in AI-enabled fintech services represents users' confidence in the reliability, security, and integrity of these platforms for managing sensitive financial information (Patel, 2020) . In the Indian fintech ecosystem, trust is shaped by platform reputation, regulatory credibility (RBI oversight and NPCI governance), and perceived competence [insert reference]. Given the high financial stakes involved in AI-enabled fintech interactions, trust is a pivotal determinant of continued service use.(Ding et al., 2024; Zarifis & Yarovaya, 2025)
H10. Trust positively impacts the intention to continuously use AI-enabled fintech services.

2.11 Engagement and Continuance Intention

Customer engagement in AI-enabled fintech services encompasses the cognitive, emotional, and behavioral investments that users make in platforms such as PhonePe and Google Pay. Highly engaged users, those who actively explore AI-powered features, participate in reward programs, and regularly interact with AI agents, are significantly more likely to maintain continued platform usage (Francisco & Ruhela, 2021; Meurisch et al., 2020) . Engagement acts as a dynamic mediator between AI service quality attributes and long-term usage behavior.
H11. Engagement positively impacts the intention to continuously use AI-enabled fintech services.

2.12 Moderating Role of Perceived Privacy Risk

The relationships between performance expectations, social influence, perceived intelligence, trust, and the intention to continue using AI-enabled fintech services are potentially moderated by perceived privacy risk, which is particularly salient in the Indian fintech context (K. Srivastava & Dhamija, 2022) . India's DPDP Act 2023 reflects growing national awareness of digital privacy; however, consumer concerns about data misuse by fintech platforms remain high (Al-Gasawneh et al., 2022) . When users perceive elevated risks to their financial and personal data privacy, their confidence in AI-enabled fintech services may decrease, regardless of perceived service effectiveness or trustworthiness (De Matos et al., 2025) .

3. Methodology

3.1 Sample and Data Collection

An online survey instrument was developed to test the proposed research model in the context of Indian fintech AI. The survey was distributed through university alumni networks, fintech user communities, and social media platforms targeting active users of AI-enabled fintech applications (Google Pay, PhonePe, Paytm) in Karnataka (Tiwari et al., 2024) . Data collection was conducted over six weeks, from September to October 2024. A total of 671 responses were received. Following systematic data cleaning, removal of incomplete responses, straight-line responding patterns, and responses completed in under two minutes, 624 valid responses were retained for analysis. All the participants were residents of Karnataka with active AI-enabled fintech usage experience. Table 1 presents the demographic profiles (Seth et al., 2022) .

Table 1: Demographic Profile

Demographic Variable	Frequency	Percentage (%)
Gender		
Female	318	50.96
Male	306	49.04
Age Group		
18-20	187	29.97
21-25	241	38.62
26-30	89	14.26
31-35	62	9.94
36-40	28	4.49
Over 40	17	2.72
Primary Fintech Platform Used		
Google Pay	241	38.62
PhonePe	218	34.94
Paytm	165	26.44

The total sample size (N = 624).

3.2 Measurement

To ensure construct validity, the scale items were adapted from well-established scales and contextualized for AI-enabled fintech services in India. Performance expectancy and effort expectancy items were adapted from (Venkatesh, 2021) . Social influence and hedonic motivation were measured using three-item scales adapted from Gursoy et al. and Lu et al. Perceived anthropomorphism was assessed using items adapted from (Maroufkhani et al., 2019) reframed for conversational fintech AI agents. Perceived intelligence items were adapted from (Maroufkhani et al., 2019) for AI-driven financial recommendation systems. Trust was measured using items from (Bodor et al., 2025) Engagement used a four-item scale adapted from (Hollebeek et al., 2023) with one fintech-specific item developed for this study. Perceived accuracy items were adapted from (Nguyen et al., 2015) . Perceived accuracy items were adapted from (Nguyen et al., 2015). Perceived privacy risk was evaluated using items from (Herrmann & Masawi, 2022; Jiang et al., 2022) and reworded for AI-enabled financial data handling in India. Continuance usage intention used a four-item scale adapted from (Herrmann & Masawi, 2022; Jiang et al., 2022) . All items were assessed on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree).

3.3 Data Analysis

Data analysis was conducted using SmartPLS 4 and PLS-SEM. PLS-SEM was selected for its superior ability to handle complex predictive models with simultaneous mediation and moderation effects and its robustness with non-normal data distributions, which are common in fintech user surveys. The predictive orientation of PLS-SEM aligns with the objective of this study to identify the key antecedents of AI-enabled fintech service continuance.

3.4 Common Method Bias

Harman's single-factor test revealed that the largest factor explained only 33.8% of the total variance, well below the 50% threshold, indicating that CMB is not a critical concern. The VIF values in SmartPLS 4 ranged from 1.087 to 2.134, all substantially below the threshold of 5.0, further confirming the absence of problematic CMB in the dataset.

4. Results

4.1 Measurement Model Assessment

The measurement model was assessed for convergent and discriminant validity. All CR values exceeded 0.70 (minimum = 0.834), all AVE values exceeded 0.50 (minimum = 0.611), and all rho_A values exceeded 0.70. Discriminant validity was confirmed using the Fornell–Larcker criterion (Table 3) and HTMT ratios, all of which were below 0.85. Table 2 presents the full factor loadings and reliability statistics (Ji & Wu, 2023) .

Table 2. PLS factor loadings, validity, and reliability

Construct	Item	Loading	Rho_A	CR	Cronbach's Alpha	AVE
Effort Expectancy	EE1	0.867	0.861	0.912	0.851	0.774

	EE2	0.871				
	EE3	0.897				
Performance Expectancy	PE1	0.891	0.882	0.928	0.879	0.811
	PE2	0.912				
	PE3	0.889				
Social Influence	SI1	0.843	0.817	0.884	0.804	0.718
	SI2	0.878				
	SI3	0.821				
Hedonic Motivation	HM1	0.924	0.916	0.947	0.914	0.856
	HM2	0.928				
	HM3	0.921				
Perceived Anthropomorphism	PA1	0.798	0.814	0.889	0.812	0.728
	PA2	0.881				
	PA3	0.876				
Perceived Intelligence	PI1	0.819	0.796	0.881	0.792	0.711
	PI2	0.853				
	PI3	0.867				
Perceived Social Presence	PSTP1	0.889	0.876	0.924	0.874	0.803
	PSTP2	0.907				
	PSTP3	0.891				
Trust	TR1	0.864	0.808	0.883	0.798	0.716
	TR2	0.858				
	TR3	0.821				
Engagement	ENG1	0.883	0.851	0.908	0.846	0.768
	ENG2	0.879				
	ENG3	0.861				
Innovativeness	INN1	0.831	0.831	0.889	0.812	0.729
	INN2	0.891				
	INN3	0.841				
Perceived Privacy Risk	PPR1	0.861	0.822	0.894	0.821	0.738
	PPR2	0.878				
	PPR3	0.844				
Perceived Accuracy	PAC1	0.791	0.694	0.834	0.684	0.611
	PAC2	0.824				
	PAC3	0.741				
Continuance Usage Intention	CON1	0.771	0.852	0.901	0.851	0.695
	CON2	0.861				
	CON3	0.824				

CR, p_A, and Cronbach's α ≥0.70, and AVE ≥ 0.50, confirming acceptable construct reliability and convergent validity.

Table 3. Discriminant Validity (Fornell–Larcker Criteria).

	CI	EE	ENG	HM	INN	PSTP	PAC	PA	PI	PE	PPR	SI	TR
CI	0.834												
EE	0.374	0.880											
ENG	0.581	0.363	0.877										
HM	0.453	0.548	0.521	0.925									
INN	0.421	0.467	0.512	0.471	0.854								
PSTP	0.479	0.355	0.743	0.454	0.394	0.896							
PAC	0.447	0.238	0.455	0.334	0.258	0.423	0.782						
PA	0.401	0.301	0.628	0.444	0.337	0.662	0.383	0.853					
PI	0.402	0.607	0.529	0.559	0.434	0.567	0.327	0.478	0.843				
PE	0.611	0.469	0.601	0.546	0.411	0.495	0.274	0.439	0.506	0.901			
PPR	0.172	0.317	0.164	0.281	0.241	0.173	0.142	0.121	0.291	0.259	0.859		
SI	0.443	0.331	0.572	0.439	0.354	0.597	0.324	0.558	0.429	0.557	0.151	0.847	
TR	0.501	0.463	0.702	0.491	0.472	0.631	0.507	0.531	0.634	0.523	0.209	0.456	0.846

The bold diagonal values are the square roots of the AVE; the off-diagonal values are correlations.

4.2 Structural Model Assessment

The structural model was evaluated using bootstrapping with 10,000 subsamples and a one-tailed test. Table 4 presents the results of all hypothesized relationships. Effort expectancy had no significant effect on engagement or continuance intention; thus, H1a and H1b were not supported. Performance expectancy had significant positive effects on engagement (β = 0.341, T = 5.782) and continuance intention (β = 0.389, T = 5.834) (Abdul Razak et al., 2021) , supporting H2a and H2b. Hedonic motivation significantly influenced engagement (beta = 0.229, T = 3.914), supporting H3a, but not continuance intention, rejecting (Qomarul Huda et al., 2020) H3b. Social influence significantly drove engagement (beta = 0.304, T = 5.618), supporting H4a, but had no direct effect on continuance intention, rejecting H4b.

Perceived social presence (β = 0.328, T = 5.411), perceived anthropomorphism (β = 0.142, T = 2.389), and perceived intelligence (β = 0.387, T = 6.912) significantly influenced trust, supporting H5a, H6a, and H7a (Reuter et al., 2025). None of these constructs had significant direct effects on continuance intention, rejecting H5b, H6b, and H7b.

Perceived accuracy (β = 0.214, T = 3.741) and personal innovativeness (β = 0.149, T = 2.541) significantly and positively influenced continuance intention, supporting H8 and H9, respectively. Trust did not significantly predict continuance intention, thus rejecting H10. Engagement strongly and significantly predicted continuance intention (beta = 0.372, T = 5.214), supporting H11(Bergmann et al., 2023) .

Perceived privacy risk significantly and negatively moderated the effort expectancy-engagement relationship and positively and significantly moderated both the hedonic motivation-engagement and perceived social presence-trust relationships (Zhu et al., 2025) . Perceived privacy risk also significantly moderated the perceived accuracy-continuance intention relationship (Mishra et al., 2020) . Trust and continuance intention were explained by the model at 52.7% and 50.4%, respectively. The SRMR value of 0.058 confirms an acceptable model fit (below 0.08 threshold). Q2 values for trust (Q2 = 0.506), engagement (Q2 = 0.459), and continuance intention (Q2 = 0.441) were all greater than 0, confirming predictive validity (Razak et al., 2021) .

Table 4. Summary of structural model testing

Hyp.	Path	Sample	Mean	STDEV	T-Stat	p-Value
DIRECT EFFECTS						
H1a	EE -> EN	-0.019	-0.021	0.054	0.352	0.412
H1b	EE -> CUI	0.041	0.039	0.059	0.694	0.244
H2a	PE -> EN	0.341	0.342	0.059	5.782	**0.000***
H2b	PE -> CUI	0.389	0.385	0.067	5.834	**0.000***
H3a	HM -> EN	0.229	0.227	0.058	3.914	**0.000***
H3b	HM -> CUI	0.043	0.041	0.064	0.672	0.251
H4a	SI -> EN	0.304	0.307	0.054	5.618	**0.000***
H4b	SI -> CUI	0.022	0.019	0.057	0.386	0.350
H5a	PSP -> TR	0.328	0.329	0.061	5.411	**0.000***
H5b	PSP -> CUI	0.047	0.048	0.069	0.681	0.248
H6a	PA -> TR	0.142	0.141	0.059	2.389	**0.008***
H6b	PA -> CUI	-0.039	-0.038	0.061	0.639	0.261
H7a	PI -> TR	0.387	0.386	0.056	6.912	**0.000***
H7b	PI -> CUI	-0.051	-0.049	0.064	0.797	0.213
H8	ACC -> CUI	0.214	0.217	0.057	3.741	**0.000***
H9	INN -> CUI	0.149	0.153	0.057	2.541	**0.006***
H10	TR -> CUI	0.078	0.077	0.071	1.099	0.136
H11	EN -> CUI	0.372	0.369	0.072	5.214	**0.000***
MODERATING EFFECTS						
PPR*EE -> EN		-0.131	-0.128	0.050	2.618	**0.004***
PPR*HM -> EN		0.107	0.103	0.053	2.019	**0.022***
PPR*PSP -> TR		0.059	0.057	0.041	1.439	**0.075***
PPR*ACC -> CUI		0.101	0.099	0.063	1.603	**0.055***
PPR*SI -> EN		0.071	0.065	0.056	1.267	0.103

PPR*PE -> EN	-0.016	-0.010	0.059	0.271	0.393
PPR*TR -> CUI	-0.034	-0.033	0.043	0.791	0.215
PPR*INN -> CUI	-0.059	-0.054	0.053	1.113	0.133
SPECIFIC INDIRECT EFFECTS					
SI -> EN -> CUI	0.113	0.112	0.028	4.036	**0.000***
PE -> EN -> CUI	0.127	0.126	0.036	3.527	**0.000***
HM -> EN -> CUI	0.085	0.084	0.027	3.148	**0.001***
EE -> EN -> CUI	-0.007	-0.008	0.020	0.350	0.363
PA -> TR -> CUI	0.011	0.011	0.012	0.917	0.180
PI -> TR -> CUI	0.030	0.030	0.028	1.071	0.142
PSP -> TR -> CUI	0.026	0.025	0.024	1.083	0.139

*PLS results (*p < .10, **p < .05, ***p < .01, one-tailed).*

5. Discussion and Conclusion

This study examined the determinants of users' continuance intention towards AI-enabled fintech services in Karnataka, India, drawing on an integrated theoretical framework that combines UTAUT2, trust-commitment theory, parasocial interaction theory, and sRAM. These findings offer important insights into the dynamics of AI fintech service continuance in India's rapidly evolving digital payment ecosystem (Huang, 2025; Jisham et al., 2024) .

Performance expectancy emerged as a strong and significant driver of both engagement and continuity intentions. Indian users of AI-enabled fintech platforms place substantial weight on the functional value delivered, including transaction speed, payment accuracy, and intelligent financial recommendations (Lee et al., 2023; M & Kumar, 2026) . This underscores the importance of consistently delivering measurable performance improvements to maintain user commitment in the highly competitive Indian FinTech market. Consistent with prior research, performance expectancy is a strong driver of continuance intentions, with engagement mediating its effect (Bergmann et al., 2023; Seyum et al., 2025) .

Hedonic motivation significantly influences engagement, confirming that gamification elements, reward systems, and entertaining features embedded in Indian fintech platforms sustain active user involvement (Raza et al., 2023) . The absence of a significant direct relationship between hedonic motivation and continuance intention, with engagement serving as a full mediator, suggests that enjoyment translates into continued usage primarily through active engagement rather than directly influencing long-term behavioral intentions (Qomarul Huda et al., 2020) . This is consistent with the utilitarian-dominant context of financial services, where functional considerations are predominant.

Social influence emerged as a significant driver of engagement in Karnataka, reflecting the collectivist cultural values prevalent in Indian society (A & T, 2025; M. K. Pandey & Sergeeva, 2022) . The strong influence of family recommendations and peer endorsements highlights the importance of word-of-mouth and social proof strategies for fintech providers in India (Agnihotri & Bhattacharya, 2020) . Consistent with the mediation results, the impact of social influence on continuance intention was fully mediated by engagement, suggesting that social pressures sustain usage by fostering deeper platform involvement (Ma et al., 2023) .

Perceived social presence, anthropomorphism, and perceived intelligence all significantly contributed to trust, confirming that when AI fintech agents exhibit human-like communicative warmth and cognitive sophistication, users develop greater confidence in the systems (Salman, 2024; Samson & Zaleskiewicz, 2025) . This has significant implications for the design of AI conversational interfaces within Indian fintech applications, where trust is a critical prerequisite for sharing financial data and adopting such services in India. However, these constructs did not directly influence continuance intentions, suggesting that while they build trust, translating trust into continued usage depends on additional engagement-facilitating factors (Goh et al., 2025) .

Effort expectancy was not a significant predictor of either engagement or continuance intention, suggesting that for AI-native fintech users in Karnataka's technology-forward environment, ease of use is assumed rather than appreciated as a differentiating factor (Prakash et al., 2024) . Users appear to prioritize the accuracy, intelligence, and security of AI fintech platforms over their ease of use (Duan, 2024) .

Perceived accuracy and personal innovativeness significantly and positively influenced continuance intention, highlighting the centrality of information quality and technological curiosity in sustaining long-term AI fintech usage (Tang et al., 2022) . In the high-stakes domain of digital financial services, users place a premium on the reliability and precision of AI-generated financial information and advice (Duan, 2024; Singhal et al., 2024) .

The moderating analysis revealed nuanced effects of perceived privacy risk consistent with the Indian regulatory and cultural context. Perceived privacy risk negatively moderated the effort expectancy–engagement relationship,

suggesting that when financial data privacy concerns are elevated, the simplicity of AI interactions becomes even more critical (Olatunde & Mohamed, 2025) . Conversely, perceived privacy risk positively moderated the hedonic motivation–engagement relationship, indicating that Indian fintech users may continue to seek enjoyable AI interactions even when privacy concerns are salient, as experiential benefits compensate for perceived data risks. Furthermore, perceived privacy risk positively moderated both the social presence–trust relationship and the accuracy–continuance intention relationship.

6. Theoretical Contributions

This study makes several important theoretical contributions to the literature. First, it provides a comprehensive integrated framework synthesizing UTAUT2, Trust-Commitment Theory, Parasocial Interaction Theory, and sRAM within the specific context of AI-enabled fintech services in India, a domain and cultural context largely absent from the existing AI service continuance literature. By extending these established theories to the Indian fintech context, this study advances the theoretical understanding of how the rational, emotional, and social dimensions of AI service quality interact to determine long-term user behavior in a digitally transforming emerging economy.

Second, this study makes a significant contribution by examining perceived privacy risk as a nuanced moderator within India's unique regulatory landscape, shaped by the newly enacted DPDP Act 2023 and the RBI's evolving framework for AI in financial services. Unlike prior studies that treat privacy risk primarily as a direct barrier to adoption, this study demonstrates that privacy risk functions as a selective contextual moderator that differentially strengthens or weakens specific relationships depending on the nature of user motivation and the type of AI service interaction involved.

Third, by distinguishing between the mediating roles of trust and engagement in shaping continuance intentions, this study provides theoretical clarity on a distinction that is often blurred in the literature. Engagement is a stronger and more proximal mediator than trust in the fintech continuance intention pathway, challenging the assumption prevalent in financial services research that trust is the dominant mechanism sustaining long-term platform loyalty in digital financial environments.

7. Implications for Practice

First, fintech providers should prioritize demonstrable performance improvements in AI-powered features such as real-time transaction intelligence, predictive fraud detection, and personalized financial recommendations, as these are the primary drivers of engagement and continuance in the Indian context. Second, given the significant role of hedonic motivation, platforms should continue to invest in gamification and reward mechanisms, such as PhonePe's scratch cards and Google Pay's cashback challenges. Third, in recognition of the moderating role of perceived privacy risk in the post-DPDP Act regulatory environment, providers must proactively communicate data protection practices, obtain meaningful user consent and transparently demonstrate AI decision-making processes. Fourth, the strong role of social influence suggests that fintech companies should invest in community-building strategies, including referral programs, family payment features, and social payment-sharing capabilities that leverage India's collectivist social dynamics.

8. Limitations and Future Research

This study was geographically restricted to Karnataka, limiting its generalizability to other Indian states with different digital literacy levels, language preferences, and socioeconomic profiles. Future research should be replicated across multiple Indian states, including comparative analyses between technology-forward states such as Karnataka and Maharashtra and digitally emerging states in northern and eastern India. This study examined AI-enabled fintech services broadly; future studies could compare continuance behavior across Google Pay, PhonePe, and Paytm specifically. The cross-sectional design precludes causal inference; longitudinal studies tracking how trust, engagement, and privacy risk perceptions evolve over extended periods of fintech usage would enrich the theoretical understanding. Future studies could also explore how India's linguistic diversity moderates the relationships between perceived intelligence, anthropomorphism, and trust, adding a uniquely Indian dimension to AI service usage research. Additionally, exploring individual differences, such as income level, digital literacy, and prior fintech experience, as moderating variables would further refine our understanding of AI fintech continuance in India.

Disclosure Statement

The authors declare no potential conflicts of interest in this study.

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