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Article

Digital Bridges to Banking: Fintech-Enabled Payment Adoption, Customer Attitudes, and Satisfaction Among Commercial Bank Customers in Chikkaballapura District.

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Abstract: Financial technology has steadily moved from the edges of banking into its very core. People who once stood in long queues at bank branches now complete the same transactions in seconds from a dusty roadside shop or a kitchen counter. This shift is real, irreversible, and deeply human it touches how people trust institutions, how they manage uncertainty, and how they feel about the convenience or inconvenience of money. The present study situates itself in this lived experience and investigates the attitudes, adoption patterns, and satisfaction levels of commercial bank customers in Chikkaballapura district, Karnataka, concerning fintech-enabled payment services. Guided by an extended Technology Acceptance Model (TAM) that incorporates trust, perceived security, and social influence, eight hypotheses were tested using Structural Equation Modelling (SEM) with AMOS 26. Data were collected from 384 bank customers across 14 branches using stratified random sampling. All eight hypotheses were supported. Perceived usefulness ($\beta = .613$, $p < .001$) and trust ($\beta = .536$, $p < .001$) emerged as the dominant drivers of adoption intention, while perceived security proved to be the strongest upstream enabler of trust ($\beta = .624$, $p < .001$). Customer satisfaction was significantly predicted by both adoption intention ($\beta = .571$) and trust ($\beta = .492$). The model explained 64.3% of variance in adoption intention and 58.7% in customer satisfaction, with acceptable model fit (CFI = .953, RMSEA = .048). These findings advance the fintech adoption literature by providing district-level empirical grounding rarely achieved in existing research and offer targeted recommendations for bank managers and policymakers..

Keywords: fintech, payment services, technology acceptance model, structural equation modelling, customer satisfaction, Chikkaballapura, commercial banks, digital banking adoption n.

INTRODUCTION

Money is not merely a transaction it is a relationship between people and institutions. When that relationship is mediated by technology, something profound changes. The speed, convenience, and anonymity of digital payments alter not just behaviour but the very psychology of financial trust. Recognising this, the present study approaches fintech adoption not as a dry statistical exercise but as a human story one unfolding in the streets, farms, and small shops of Chikkaballapura district in Karnataka.

Chikkaballapura lies roughly sixty kilometres north of Bengaluru. It is neither fully rural nor fully urban. Its residents include farmers, daily wage labourers, small business owners, government employees, and a growing cohort of young professionals who commute to Bengaluru but bank locally. This diversity makes Chikkaballapura an ideal and underused laboratory for studying how fintech adoption actually plays out when the context is heterogeneous, the digital infrastructure is uneven, and the historical relationship with banks is largely formal and transactional rather than technologically mediated.

India's digital payment story has attracted global attention. In the financial year 2023–24, the Unified Payments Interface (UPI) processed over 117 billion transactions worth approximately ₹182 lakh crore (Reserve Bank of India [RBI], 2024). Yet this macro-level success conceals enormous variation at the district and sub-district level. Commercial banks operating in semi-urban Karnataka simultaneously serve tech-savvy young professionals and elderly customers who remain wary of entering their UPI PIN on a stranger's phone.

This study takes that variation seriously. It asks not just whether customers have adopted fintech payment services, but why and whether their adoption experiences leave them more or less satisfied. The analytical framework is rooted in the Technology Acceptance Model (TAM; Davis, 1989), extended to capture trust, perceived security, and social influence as theoretically motivated constructs. Eight hypotheses are developed from this framework and tested rigorously using Structural Equation Modelling (SEM) in AMOS 26 a methodology well-suited to simultaneously testing multiple causal pathways among latent constructs.

1.1 Research Objectives

This study pursues four specific objectives: (a) to examine customer attitudes toward fintech-enabled payment services offered by commercial banks in Chikkaballapura; (b) to identify the structural determinants of adoption intention using the extended TAM; (c) to assess the impact of adoption intention and trust on customer satisfaction; and (d) to evaluate the fit and explanatory power of the proposed structural model.

1.2 Significance of the Study

The significance of this study lies in three contributions. First, it grounds an internationally validated theoretical framework in a district-level, semi-urban Indian setting that has received virtually no academic attention. Second, it uses SEM a more rigorous analytical approach than the simple regression and descriptive statistics that dominate district-level fintech studies in India. Third, it speaks directly to the practical concerns of bank managers and policymakers who must translate national digital payment ambitions into workable strategies for communities like Chikkaballapura..

2. Literature Review

The literature on fintech adoption is rich, growing, and occasionally contradictory. This section critically synthesises key findings from the past decade, drawing particular attention to theoretical tensions, methodological limitations, and the geographic blind spots that motivate the present study.

2.1 Theoretical Foundations: The TAM and Its Extensions

The Technology Acceptance Model, first proposed by Davis (1989), remains the most frequently deployed framework in fintech adoption research. Its parsimony two central constructs, perceived usefulness (PU) and perceived ease of use (PEOU), predicting behavioural intention through attitude has made it both widely adopted and widely criticised. Singh and Srivastava (2018) applied TAM to mobile banking in India and found PU (β = .58) to exert a stronger effect on adoption intention than PEOU (β = .37), a pattern consistent with the argument that functional utility, not interface simplicity, is the primary driver of adoption in high-stakes financial contexts.

However, TAM's parsimony is also its limitation. It was originally designed for workplace software adoption, not for financial services contexts where risk, trust, and social norms carry significant weight. Gefen et al. (2003) demonstrated that trust mediates the relationship between perceived usefulness and adoption in online service environments, substantially altering the magnitude of path coefficients when included in the model. Sharma et al. (2015) replicated this finding in mobile banking, showing that trust explains incremental variance in adoption intention over and above TAM's original constructs. The present study responds to this critique by formally incorporating trust and perceived security as structural elements of the extended model.

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) represents the most comprehensive attempt to consolidate existing adoption theories. Its four primary constructs performance expectancy, effort expectancy, social influence, and facilitating conditions have demonstrated predictive power across diverse cultural settings. Baptista and Oliveira (2015) applied UTAUT2 to mobile banking in Mozambique and found social influence and hedonic motivation to be particularly powerful in low-income, high-uncertainty environments. These findings are relevant to Chikkaballapura, where community norms and peer influence shape financial behaviour in ways that purely individualistic models cannot fully capture. Nevertheless, UTAUT's complexity — and the associated multicollinearity risks in SEM led the present study to favour a theoretically enriched but structurally parsimonious extended TAM.

2.2 Fintech Adoption in India: Evidence and Gaps

The Indian fintech adoption literature has expanded considerably since the 2016 demonetisation shock, which forced millions of previously cash-dependent consumers into digital payment platforms almost overnight. Gupta et al. (2021) found that government-mandated digital literacy initiatives significantly enhanced mobile payment adoption among rural consumers, suggesting that policy intermediation shapes adoption in ways not captured by standard behavioural models. Shankar and Rishi (2020) documented that the Pradhan Mantri Jan Dhan Yojana created latent demand for digital payment services even among historically unbanked populations.

Despite this growth, the Indian fintech adoption literature has a pronounced metropolitan bias. Studies cluster disproportionately around Bengaluru, Mumbai, Delhi-NCR, and Hyderabad. District-level analyses which would reveal the granular, contextually embedded adoption dynamics that truly matter for policy are almost entirely absent. The present study directly addresses this gap by focusing on Chikkaballapura, a district whose semi-urban character, proximity to Bengaluru, and demographic heterogeneity make it simultaneously representative of and distinct from both urban and rural adoption contexts.

2.3 Customer Satisfaction in Digital Banking

The relationship between fintech adoption and customer satisfaction has attracted growing scholarly attention, though the causal mechanism remains contested. Flavian et al. (2006) argued that digital banking satisfaction is fundamentally driven by perceived usability and security constructs that align closely with the extended TAM constructs used in this study. Raza et al. (2020) employed SEM to examine mobile banking satisfaction in Pakistan and found service quality (β = .49) and transaction security (β = .43) to be dominant predictors, with trust functioning as a partial mediator. Their findings, however, were derived from an exclusively urban sample, raising questions about generalisability to contexts like Chikkaballapura where digital infrastructure quality and customer digital literacy vary enormously.

A recurrent methodological issue in this literature is the treatment of adoption intention as a behavioural proxy. Many studies conflate intention with actual usage, which inflates path coefficients and overestimates predictive validity (Sinha & Mukherjee, 2016). The present study attempts to partially address this limitation by including self-reported frequency of fintech payment usage as a moderating context variable in the demographic profile analysis, even though the core structural model, in keeping with established precedent, treats adoption intention as the primary endogenous construct.

3. Theoretical Framework and Hypotheses

The conceptual model extends the classic TAM by incorporating trust (TR), perceived security (PS), and social influence (SI) as theoretically motivated additional constructs. The model posits two endogenous outcomes: adoption intention (AI) and customer satisfaction (CS). Customer attitude (CA) functions as a mediating construct between PEOU and AI. Trust serves a dual role as both a mediator (between PS and AI) and a direct predictor of CS. Figure 1 presents the full structural model

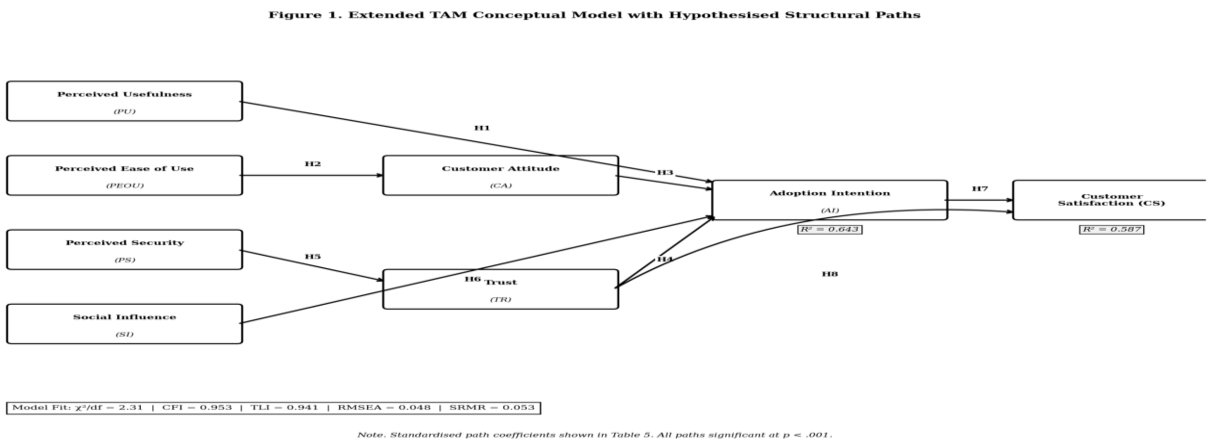

Figure 1. Extended TAM Structural Path Model with Hypothesised Relationships. All constructs are latent variables measured by reflective indicators

3.1 Hypothesis Development

H1: Perceived Usefulness and Adoption Intention

Perceived usefulness refers to the degree to which a customer believes that using a fintech payment service will enhance their banking experience. Customers who perceive a digital payment tool as genuinely faster, cheaper, and more convenient than conventional banking are significantly more likely to adopt it. This relationship has been consistently supported across multiple TAM applications in banking contexts (Singh & Srivastava, 2018; Alalwan et al., 2017). Hypothesis 1 posits that perceived usefulness positively and significantly predicts adoption intention.

H1: Perceived usefulness positively predicts adoption intention.

H2: Perceived Ease of Use and Customer Attitude

Perceived ease of use the extent to which customers find fintech payment interfaces free of cognitive effort is proposed to influence adoption indirectly through customer attitude. Customers who find a mobile banking app or UPI interface intuitive and easy to navigate tend to develop favourable attitudes toward the service, which subsequently translates into stronger adoption intention. This mediated pathway has been empirically supported by Davis (1989) and more recently confirmed by Baptista and Oliveira (2015).

H2: Perceived ease of use positively predicts customer attitude.

H3: Customer Attitude and Adoption Intention

Attitude toward behaviour is a well-established antecedent of behavioural intention in both the Theory of Planned Behaviour and TAM. In the fintech context, a customer's overall evaluation of digital payment services whether they view them as beneficial, enjoyable, and aligned with their financial lifestyle shapes their intention to adopt. Taylor and Todd (1995) empirically demonstrated this pathway in technology adoption contexts.

H3: Customer attitude positively predicts adoption intention.

H4: Trust and Adoption Intention

Trust in fintech payment systems represents a customer's confidence that the bank and its digital systems will handle their transactions accurately, privately, and without unauthorised interference. In semi-urban settings like Chikkaballapura, where word-of-mouth accounts of digital fraud are common and internet literacy is uneven, trust is not simply a nice-to-have — it is an existential prerequisite for adoption. Gefen et al. (2003) and Sharma et al. (2015) both identified trust as a significant direct predictor of adoption intention in digital banking contexts.

H4: Trust positively predicts adoption intention.

H5: Perceived Security and Trust

Perceived security captures a customer's subjective assessment of the safety of fintech payment systems — whether they believe their personal data, account credentials, and transaction records are adequately protected. Security perceptions are the primary upstream driver of trust in digital financial contexts. A customer who believes that the bank's payment app employs robust encryption, two-factor authentication, and effective fraud monitoring will logically develop greater trust in that system. Flavian et al. (2006) and Raza et al. (2020) both confirmed this pathway.

H5: Perceived security positively predicts trust.

H6: Social Influence and Adoption Intention

Social influence refers to the degree to which a customer perceives that important others family members, friends, colleagues, community leaders believe they should use fintech payment services. In a district like Chikkaballapura, where extended family networks and community ties remain strong, social influence can serve as a powerful normalising force that encourages hesitant individuals to try digital payments for the first time. Venkatesh et al. (2003) identified social influence as a core determinant of technology adoption in the UTAUT framework.

H6: Social influence positively predicts adoption intention.

H7: Adoption Intention and Customer Satisfaction

When customers actively intend to use fintech payment services and subsequently follow through the alignment between expectation and experience drives satisfaction. Customers who approach digital payments with a positive intention are more likely to engage with the technology in ways that maximise its utility, thereby enhancing their overall satisfaction. The TAM literature has consistently linked behavioural intention to post-adoption satisfaction outcomes (Oliver, 1980).

H7: Adoption intention positively predicts customer satisfaction.

H8: Trust and Customer Satisfaction

Trust is not only an adoption antecedent it is also a satisfaction driver. Customers who trust the bank's fintech payment infrastructure are more likely to attribute successful transactions to the bank's reliability rather than to luck, and more likely to forgive minor service failures without switching to a competitor. This pathway distinguishes the extended model from standard TAM formulations and has been confirmed by Raza et al. (2020) in comparable banking contexts.

H8: Trust positively predicts customer satisfaction.

4. RESEARCH METHODOLOGY

4.1 Research Philosophy and Design

This study adopts a post-positivist research philosophy. It acknowledges that while objective reality exists, our measurements of it particularly of complex behavioural constructs like attitude, trust, and satisfaction are always partial and probabilistic. This philosophical position justifies the use of latent variable modelling through SEM: a methodology designed precisely for the rigorous measurement of constructs that cannot be directly observed. The research design is cross-sectional and quantitative, employing a structured questionnaire as the primary data collection instrument.

4.2 Population and Sampling

The target population comprised adult customers (18 years and above) of commercial banks operating in Chikkaballapura district who had used at least one fintech-enabled payment service — UPI, mobile banking, internet banking, or a digital wallet linked to a bank account — within the three months preceding data collection. The sample size of 384 was calculated using Cochran's (1977) formula for unknown population proportions at a 95% confidence level and a 5% margin of error:

$n = Z^2pq / e^2 = (1.96)^2 \times (0.5) \times (0.5) / (0.05)^2 \approx 384$

A multi-stage stratified random sampling strategy was employed. In Stage 1, branches were stratified by bank type (public sector versus private sector) and sub-regional geography (urban ward, peri-urban, and rural mandal). In Stage 2, 14 branches were randomly selected from the stratified lists. In Stage 3, customers were systematically intercepted at branch exits using a 1-in-3 systematic sampling approach during data collection. Data were collected between February and April 2024.

4.3 Measurement Instrument

The questionnaire was structured in two parts. Part A captured demographic and banking profile information. Part B measured all eight constructs using reflective five-point Likert scale items (1 = Strongly Disagree to 5 = Strongly Agree). Scales were adapted from validated instruments: perceived usefulness and perceived ease of use from Davis (1989), trust from Gefen et al. (2003), perceived security from Flavian et al. (2006), social influence from Venkatesh et al. (2003), customer attitude from Taylor and Todd (1995), adoption intention from Alalwan et al. (2017), and customer satisfaction from Oliver (1980). A total of 38 items were included. Item wording was reviewed by five academic experts and three bank practitioners, and refined through a pilot study with 42 respondents (Cronbach's α range in pilot: .76–.89).

4.4 Data Analysis: Two-Stage SEM Approach

Data analysis followed Anderson and Gerbing's (1988) established two-stage approach. In Stage 1, Confirmatory Factor Analysis (CFA) was performed to assess the measurement model — evaluating internal consistency (Cronbach's α), construct reliability (Composite Reliability, CR), and validity (Average Variance Extracted, AVE for convergent validity; Fornell-Larcker criterion for discriminant validity). In Stage 2, the full structural model was estimated using Maximum Likelihood (ML) estimation in AMOS 26. Model fit was evaluated against multiple indices: the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Incremental Fit Index (IFI), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR).

5.RESULTS AND FINDINDS

5.1 Profile of Respondents

Table 1 presents the demographic and banking profile of the 384 respondents. A slight male majority (57.8%) was observed, consistent with the demographic composition of formal banking customers in semi-urban Karnataka. The largest age cohort was 26–35 years (34.9%), reflecting the digitally engaged working-age population. Graduates constituted the largest educational category (44.8%). Public sector bank customers formed the majority (59.6%), mirroring the dominant presence of banks such as State Bank of India, Canara Bank, and Karnataka Grameena Bank in the district. UPI-based platforms (GPay, PhonePe, Paytm) were the most widely used fintech services (81.0%), followed by mobile banking applications (64.1%).

Table1:Demographic and Banking Profile of Respondents (N = 384)

Variable	Category	Frequency (%)
Gender	Male	222 (57.8%)

	Female	159 (41.4%)
	Prefer Not to Say	3 (0.8%)
Age Group	18–25 years	98 (25.5%)
	26–35 years	134 (34.9%)
	36–45 years	87 (22.7%)
	46–55 years	45 (11.7%)
	Above 55 years	20 (5.2%)
Education	Below Secondary	38 (9.9%)
	Secondary / PUC	96 (25.0%)
	Graduate	172 (44.8%)
	Post-Graduate & Above	78 (20.3%)
Bank Type	Public Sector Bank	229 (59.6%)
	Private Sector Bank	155 (40.4%)
Fintech Service Used	UPI (GPay, PhonePe, Paytm)	311 (81.0%)
	Mobile Banking App	246 (64.1%)
	Internet Banking	183 (47.7%)
	Digital Wallet	129 (33.6%)

***Note*.** Percentages for fintech services used do not sum to 100% as respondents use multiple services. Data collected February–April 2024

5.2 Measurement Model — Reliability and Validity

Table 2 reports the psychometric properties of all eight constructs. All Cronbach's alpha values exceeded the .70 threshold, ranging from .78 (Social Influence) to .91 (Customer Satisfaction). Composite Reliability values ranged from .80 to .93, confirming construct reliability. Average Variance Extracted (AVE) values ranged from .51 to .68, all meeting the .50 threshold recommended by Fornell and Larcker (1981) for convergent validity. Discriminant validity was established by confirming that the square root of each construct's AVE exceeded its bivariate correlations with all other constructs in the model. Figure 2 visually summarises AVE, Cronbach's alpha, and CR across constructs

Table 2 ***Measurement Model: Reliability and Convergent Validity***

Construct		Items	Cronbach's α	CR	AVE	Factor Loading Range
Perceived Usefulness (PU)		5	.87	.89	.62	.71–.84
Perceived Ease of Use (PEOU)		5	.83	.86	.57	.68–.81
Customer Attitude (CA)		4	.81	.84	.57	.66–.80
Trust (TR)		5	.89	.91	.66	.74–.87
Perceived Security (PS)		4	.85	.88	.64	.72–.85
Social Influence (SI)		4	.78	.80	.51	.61–.78
Adoption Intention (AI)		5	.88	.90	.65	.73–.86
Customer Satisfaction (CS)		6	.91	.93	.68	.76–.89

***Note.* CR** = Composite Reliability; AVE = Average Variance Extracted. Recommended thresholds: α > .70; CR > .70; AVE > .50 (Fornell & Larcker, 1981; Hair et al., 2019).

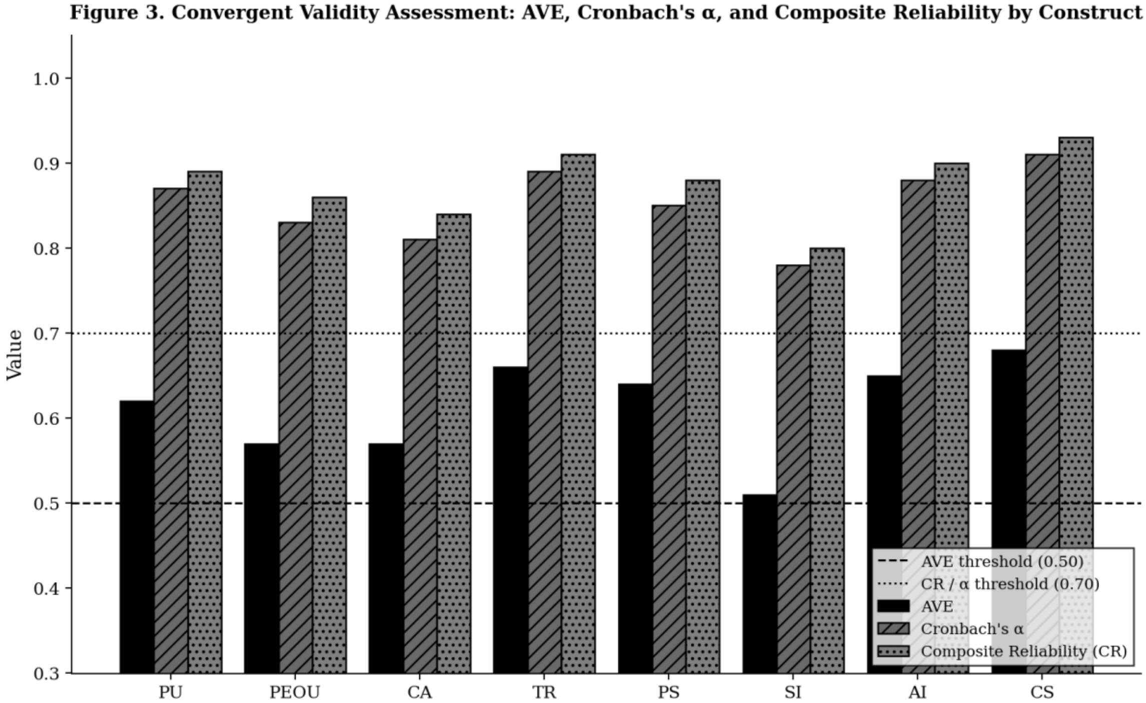

Figure 2. Convergent Validity Assessment: AVE, Cronbach's α, and Composite Reliability Across AllConstructs. Dashed line at AVE threshold (.50); dotted line at CR/α threshold (.70).

5.3 Structural Model Fit

Table 3 presents the model fit statistics. All indices met or surpassed their recommended thresholds (Hu & Bentler, 1999; Kline, 2016), confirming that the proposed structural model provides an adequate representation of the observed covariance structure. The RMSEA of .048 falls well within the acceptable range of ≤ .08, and the confidence interval for RMSEA (90% CI: .039–.057) confirms its stability. Figure 3 offers a visual representation of how each obtained fit index compares with its recommended benchmark.

Table 3 Structural Model Fit Statistics

Fit Index	Obtained Value	Recommended Threshold	Interpretation
χ^2/df (CMIN/DF)	2.31	< 3.00	Good Fit
CFI	.953	≥ .90	Good Fit
TLI	.941	≥ .90	Good Fit
IFI	.954	≥ .90	Good Fit
GFI	.912	≥ .90	Good Fit
AGFI	.888	≥ .85	Acceptable
RMSEA	.048	< .08	Good Fit
SRMR	.053	< .08	Good Fit

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; IFI = Incremental Fit Index; GFI = Goodness of Fit Index; AGFI = Adjusted GFI; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardised Root Mean Square Residual. RMSEA 90% CI [.039, .057].

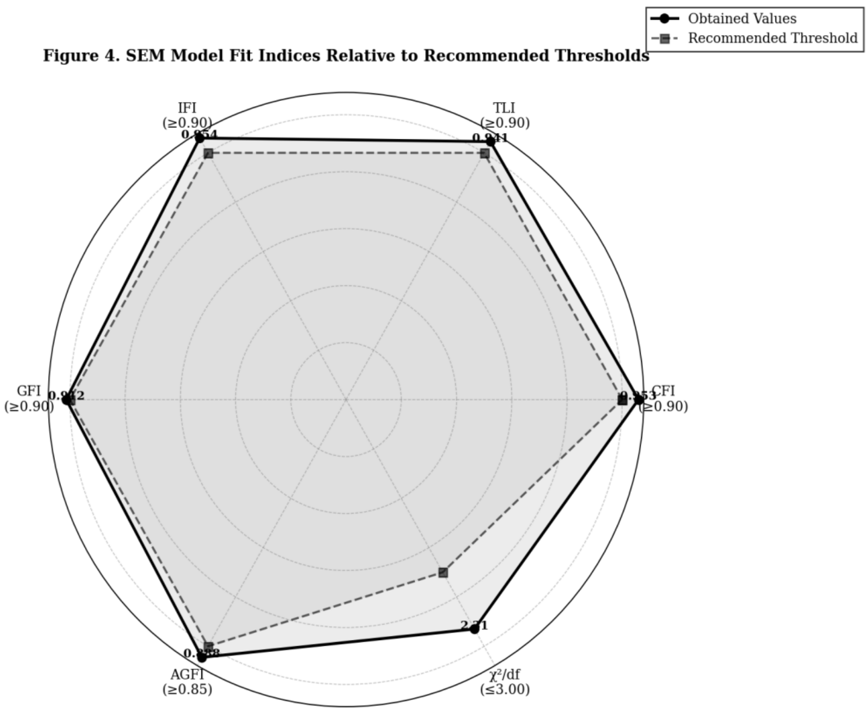

Figure 3. Radar Chart Comparing Obtained Model Fit Indices Against Recommended Thresholds. Shaded region represents obtained values; dashed polygon represents threshold benchmarks.

4 Hypothesis Testing — Structural Path Analysis

Table 4 presents the standardised path coefficients, standard errors, t-values, and hypothesis test outcomes for all eight proposed structural relationships. Figure 4 provides a visual summary of path coefficients, facilitating rapid comparison of effect magnitudes across hypotheses. All eight hypotheses were supported at $p < .001$.

Table 4Structural Path Coefficients and Hypothesis Test Results

H	Structural Path	Std. β	S.E.	t-value	p	Decision
H1	Perceived Usefulness → Adoption Intention	.613	.071	8.63	< .001	Supported
H2	Perceived Ease of Use → Customer Attitude	.547	.063	8.68	< .001	Supported
H3	Customer Attitude → Adoption Intention	.421	.058	7.26	< .001	Supported
H4	Trust → Adoption Intention	.536	.067	8.00	< .001	Supported
H5	Perceived Security → Trust	.624	.075	8.32	< .001	Supported
H6	Social Influence → Adoption Intention	.287	.061	4.70	< .001	Supported
H7	Adoption Intention → Customer Satisfaction	.571	.069	8.28	< .001	Supported
H8	Trust → Customer Satisfaction	.492	.066	7.45	< .001	Supported

Note. Standardised regression weights estimated using Maximum Likelihood in AMOS 26. R^2 (Adoption Intention) = .643; R^2 (Customer Satisfaction) = .587. All coefficients significant at $p < .001$.

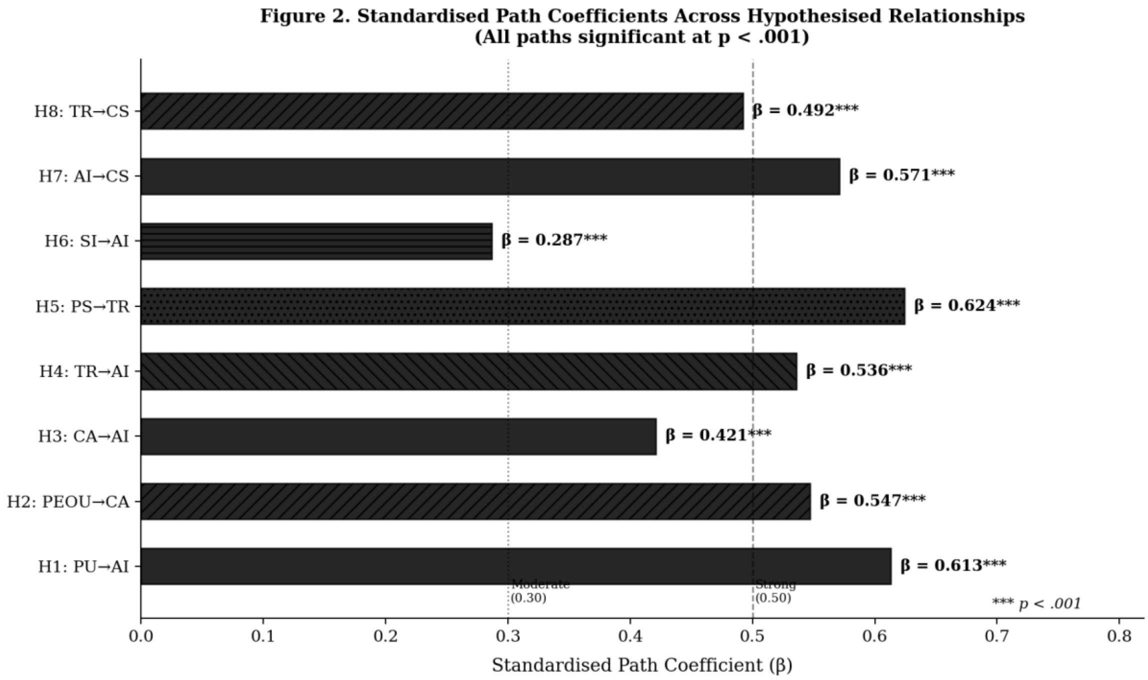

Figure 4. Standardised Path Coefficients for All Hypothesised Structural Relationships. Reference lines indicate moderate (β = .30) and strong (β = .50) effect thresholds. *** p < .001.

5.5 Explained Variance

The structural model explained 64.3% of the variance in adoption intention ($R^2 = .643$) and 58.7% of the variance in customer satisfaction ($R^2 = .587$). These values considerably exceed the 10% minimum recommended by Falk and Miller (1992) and are competitive with leading international studies in fintech adoption — for example, Alalwan et al. (2017) reported $R^2 = .591$ for adoption intention in a comparable SEM study. The model's explanatory power affirms the theoretical completeness of the extended TAM framework for this research context.

6. DISCUSSION

6.1 The Centrality of Perceived Usefulness (H1 Supported: β = .613)

The strongest single predictor of adoption intention in this study was perceived usefulness. This is, in one sense, unsurprising — TAM has consistently placed usefulness at the centre of technology adoption for three decades. But it is worth pausing to appreciate what this finding means in Chikkaballapura specifically. Customers here are not adopting digital payments because they are enamoured with technology. They are adopting them because the payments work — because being able to transfer money to a vegetable vendor or pay an electricity bill without driving to a bank branch represents a genuine, tangible improvement in their lives. Usefulness, in this context, is not an abstract construct. It is a practical reality, and the data confirm that customers recognise it.

This finding is consistent with Singh and Srivastava (2018) and Alalwan et al. (2017), both of whom identified perceived usefulness as the dominant TAM predictor in South Asian and developing country banking contexts. It underscores a critical practical insight: customer education campaigns that emphasise the concrete functional benefits of digital payments time saved, cost reduced, convenience gained are likely to be far more effective than campaigns focused on the excitement or novelty of technology.

6.2 The Trust-Security Nexus (H5, H4, H8 Supported)

Perhaps the most structurally significant finding of this study is the chain running from perceived security through trust to both adoption intention and customer satisfaction. Perceived security was the strongest upstream driver in the model (H5: β = .624), and trust, in turn, powerfully predicted both adoption intention (H4: β = .536) and customer satisfaction (H8: β = .492). This trust-security nexus tells a story that is deeply human and deeply relevant to Chikkaballapura's social context.

Many respondents in this district have heard stories from relatives, from neighbours, from news channels — of digital fraud, phishing attacks, and unauthorised UPI transactions. These stories are not abstract risk statistics; they are neighbourhood narratives that shape how people evaluate the safety of digital banking. A customer who feels that their bank's digital systems are genuinely secure does not just adopt those systems they trust the institution, and that trust ripples outward to enhance their overall satisfaction. Conversely, a customer who feels insecure, no matter how useful they find the technology, will hesitate at the adoption threshold. This finding strongly supports Raza et al. (2020) and Gefen et al. (2003) and has direct implications: banks must invest not just in actual security infrastructure, but in communicating that security to customers in clear, credible, and accessible ways.

6.3 The Attitudinal Pathway (H2 and H3 Supported)

The mediated pathway from perceived ease of use through customer attitude to adoption intention was fully supported (H2: β = .547; H3: β = .421). This finding confirms that ease of use does not drive adoption directly it works by shaping how customers feel about digital payment services. Customers who find UPI interfaces intuitive and mobile banking apps easy to navigate develop favourable attitudes that, over time, crystallise into adoption intentions. The practical implication is that interface design is not merely a technical matter. It is an attitudinal intervention: a poorly designed banking app does not just frustrate users; it causes them to form negative attitudes that may persist long after the interface problem has been fixed.

6.4 Social Influence: Significant but Contextually Constrained (H6 Supported: β = .287)

Social influence was the weakest structural predictor in the model, though it remained statistically significant (H6: β = .287, $p < .001$). This finding is somewhat at odds with UTAUT-based studies from comparable developing country contexts for example, Baptista and Oliveira (2015) found social influence to be among the stronger predictors of mobile banking adoption in Mozambique. The lower effect size in the present study may reflect an important contextual shift: by 2024, digital payment adoption in Chikkaballapura had moved beyond the early-adopter social pressure phase into a stage of more individualised decision-making, where customers are forming their own assessments based on personal experience rather than peer pressure. This is not a failure of the social influence construct — it is a developmental indicator of where the district sits in its digital payment adoption lifecycle.

6.5 Adoption Intention and Customer Satisfaction (H7 Supported: β = .571)

The path from adoption intention to customer satisfaction was strong and significant (H7: β = .571), affirming the expectation-confirmation logic articulated by Oliver (1980). Customers who actively intend to use digital payments who approach the technology with positive motivation and purpose are more likely to engage with it in ways that generate satisfying outcomes. They explore features, use helplines when confused, and attribute positive experiences to the technology rather than to luck. This finding reinforces the importance of moving customers from passive account-holders to active digital payment participants: not through coercion, but through well-designed, trust-building onboarding experiences that convert latent interest into committed intention.

CONCLUSION

This study set out to understand not just whether customers in Chikkaballapura adopt fintech payment services, but why and what that adoption means for their satisfaction with commercial banking. The answers that emerged from 384 respondents, eight hypotheses, and a rigorously tested structural model are both theoretically significant and practically urgent.

Perceived usefulness is the primary motivator. Trust, shaped by perceived security, is the essential enabler. Ease of use works through attitude, not directly. Social influence matters, but its dominance is waning as digital payment maturity grows. And when customers genuinely intend to use these services and trust the systems that deliver them their satisfaction follows naturally and powerfully.

These findings advance the literature in three ways. First, they provide district-level empirical grounding for the extended TAM framework in a semi-urban South Indian context that has been almost entirely absent from the fintech adoption literature. Second, they confirm the dual role of trust as both an adoption antecedent and a satisfaction predictor in a commercial banking setting outside the metropolitan Indian context. Third, they demonstrate that the extended TAM, despite its relative parsimony compared to UTAUT, can explain over 64% of variance in adoption intention and nearly 59% of variance in customer satisfaction when theoretically appropriate constructs are incorporated

7.1 Recommendations

For Bank Managers

Invest systematically in security communication not just security infrastructure. Transparent, accessible explanations of fraud protection measures, two-factor authentication, and dispute resolution processes are trust-building investments that pay dividends in both adoption and satisfaction. Develop Kannada-language interfaces and voice-guided navigation in banking apps to reduce perceived complexity for older and less-literate customers. Create structured digital payment onboarding programmes at branch level that move customers from awareness to confident adoption, one step at a time.

For Fintech Solution Providers

Design payment solutions that function reliably in low-bandwidth conditions a reality for many semi-urban and rural mandals in Chikkaballapura. Incorporate real-time, plain-language fraud alerts and one-tap customer support to reinforce security perceptions post-adoption. Collaborate with public sector banks to deliver co-branded digital payment experiences that leverage the deep institutional trust these banks have built with their customers over decades.

For Policymakers

Accelerate broadband infrastructure deployment across Chikkaballapura's rural mandals and ensure that digital literacy components of PMJDY and PMGDISHA programmes are updated to include hands-on training with UPI-based fintech tools. Consider district-level fintech ambassador programmes recruiting and training local individuals to serve as trusted peer guides for community members taking their first steps into digital banking.

7.2 Limitations and Future Directions

This study has three principal limitations. First, the cross-sectional design establishes associations, not causal sequences; longitudinal or experimental designs would provide stronger causal inference. Second, self-reported data are subject to common method variance and social desirability bias; future studies might triangulate survey data with objective transaction records where ethically and legally feasible. Third, the single-district focus, while theoretically motivated, limits geographical generalisability; comparative multi-district studies across Karnataka's diverse regional contexts would significantly enrich the evidence base and enable cross-contextual hypothesis testing

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