International Journal of Accounting and Economics Studies, 12 (1) (2025) 10-18

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/gzyjat18
Research paper

Exploring the factors determining fintech adoption among Indian users integrating Theory of Planned Behaviour (TPB) and Social Learning Theory (SLT)

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Received: March 12, 2025, Accepted: April 8, 2025, Published: April 13, 2025

Abstract

Even though the number of Financial Technology (Fintech) services is on the rise, the behavioural and psychological factors of how the user's intent remains to a key focus point of research. (In 2020, Rahardjo et al.) This research proposes a comprehensive model for understanding Fintech adoption in India, integrating the Theory of Planned Behaviour (TPB) and Social Learning Theory (SLT). The three TPB constructs, attitude, Subjective norms, and perceived behavioural control (PBC), serve as key determinants of behavioural intention (Gao, Y., & Tang, Y., 2023). Conversely, SLT enhances this paradigm by incorporating elements of social influence, observational learning, and reinforcement mechanisms, thus bringing to light how consumers come to establish confidence and trust in Fintech services. By incorporating various theoretical perspectives, this study aims to provide a comprehensive understanding of the influence of social and individual factors on consumer intentions towards Fintech adoption, as these factors interact in determining behavior. The study is quantitative using survey data from 462 sample responses analysed using Structural Equation Modelling (SEM) through AMOS software. The findings suggest that although social influence and observational learning are key factors influencing user perceptions, both attitude and perceived behavioural control are significantly influential on behavioral intention. Also, intention mediated the relationship between TPB constructs and adoption of Fintech services, while privacy risk moderated the relationship between intention and adoption in digital financial services. These findings emphasize how social learning dynamics, techniques of trust-building are promoting Fintech acceptance among Indian users. This research enhances existing knowledge by incorporating behavioural and psychological viewpoints and is beneficial for financial institutions, legislators, and Fintech firms who seek to promote the usage of digital financial services.

Keywords: *Fintech Adoption; Theory of Planned Behaviour; Social Learning Theory; Behavioural Intention; Observational Learning.*

1. Introduction

Although Fintech services have chosen such way of great development, the detailed behavioural and psychological determinants of Fintech user intention still lack attention (Peong et al., 2021). As Rahardjo et al. (2020); understand, these dynamics can be crucial for developing successful adoption practices. To develop an integrated model. This study expands current understanding by examining the factors influencing Fintech adoption in the Indian economy, utilizing the Theory of Planned Behaviour (TPB) and Social Learning Theory (SLT). Zhou Ayoungman et al., 2021. Within the TBP framework, attitude, subjective norms, and perceived behavioural control (PBC) serve as key determinants of behavioural intention, these are fundamental factors shaping behavioural intentions. The model is later complemented by the introduction of the social learning theory (SLT), which adds the components of social influence, observational learning, and reinforcement mechanisms, providing a better understanding of how consumers gain confidence and trustworthiness in Fintech services. This explains the harmonization of some theoretical approaches adopted by the study that would add to the discourse on how these social and individual concerns interact with consumers' intention to adopt Fintech (Nur & Dewanto, 2022). A quantitative methodology is employed with the analysis of survey data from over 456 respondents using Structural Equation Modelling (SEM). The findings are that social influence and observational learning play a crucial role in shaping user perceptions, and attitude and PBC exert a greater influence on behavioural intention. (Suci Ratnawati; Yusuf Durachman; Angga Saputra 2022 ll.,) On top of this, the study found that the relationship between TPB predictors and actual Fintech adoption also runs through a behavioural intention mediator, and that privacy risk in digital financial services is a moderator in the intention-adoption nexus, as well. These insights highlight the role of social learning dynamics, trust-building strategies, and regulatory frameworks in driving the adoption of Fintech. It also adds to the literature by incorporating psychological and behavioural facets and provides practical implications for financial institutions, policymakers, and Fintech firms seeking to increase the adoption of digital financial services. Additionally, the findings of this study have important implications for market dynamics and regulatory frameworks, beyond individual user behaviours. Such a multifaceted framework enhances consumer trust but also drives higher adoption rates towards innovative financial products, fuelling sector expansion. With user-friendly interfaces and customer support services helping make this transfer seamless, this means even the least technically savvy person will be able to navigate the digital world. Policy makers, as well as Fin Tech companies that want to contribute to increased adoption of digital financial services. Digital acceptance level of individuals can vary in terms of payment orders or account balances based on how this technology is, implying that governments should focus on upgrading digital skills first, followed by granting equal access opportunities to advance financial inclusion. Additionally, with trust being a critical factor driving adoption and use, trust-building initiatives with consumers about security measures and benefits through the Fintech ecosystem can be vital to dispelling apprehensions regarding digital transactions. (Singh et al., 2020). The current manuscript is structured such that the first component is the drivers of importance for the Fintech services and the behavioural and psychological determinants affecting the Fintech adoption. The section that follows details the literature underpinning the hypotheses developed, as well as the methodologies used in the present analysis. The third and fourth segments present extensive statistical data analysis along with a discussion and conclusions, including examination of theoretical and practical implications.

2. Review of literature

The adoption of Fintech services has been approached using several theoretical models, such as the two theories named TBP, SLT (Theory of Planned Behaviour) Social Learning Theory), etc. This research is a literature review on some determinants affecting Fintech adoption and the mediators and moderators that can influence the behaviour of users and consequently the adoption of these services. In the context of FinTech, Perceived Usefulness denotes the belief that FinTech services enhance the effectiveness of financial transactions and lead towards efficiency, affordability, and convenience (Zhou, 2011). PU has a significant effect on Fintech as studies show that users are more likely to adopt Fintech when the PU is higher (Lai, 2017). Peer referrals, social norms, and digital word-of-mouth affect an individual's decision-making process, lending insight into Fintech adoption (Slade et al., 2015). Research by Wang et al. As stated by (2019), Fintech users in the emerging markets, for example, India and Jordan, have a strong influence on their social circles. Research shows that technology adoption increases when users feel more in control of the technology (Hanafizadeh et al., 2014). Empirical studies of Abrahão et al. (2016) and Yuen et al. (2020) validate of BH users transitioning to full Fintech adoption. Several research in the context of Fintech show that if the subject deems the services useful or meaningful, after using the Fintech services will create an intention towards adopting it (Chen & Li, 2017) or they generate an intention influenced by the peer before the actual beach adoption (Lu et al., 2011). Digital financial services are greatly influenced by privacy issues (Kshetri, 2021). Based on the result and existing literature, we expect that interest in privacy risks moderates the BI → Fintech Adoption relationship, such as higher concern on privacy risk reduces the intention-to-adoption path (Featherman & Pavlou, 2003; Shin, 2010). Vulnerability related to financial data leads customers to refuse Fintech services in spite of firm Behavioural intentions (Slade et al., 2015). Having explored the literature, some direct, mediate, and moderating constructs exist that influence the acceptance of Financial Technology (Fintech). While PU, SI, and PBC significantly explain Behavioural intention, privacy risk remains an important barrier. Devi, S. (2023). Devi (2023 examines the influence of digital innovations on financial inclusion in India. Digital technologies, including mobile banking, fintech solutions, and digital payment systems, have the potential to revolutionize financial services and expand access to underserved populations. Meganathan, in his 2024 paper, explores the role of the Unified Payments Interface (UPI) in increasing the penetration of digital financial services in rural India. (Al-Smadi & Al-Smadi, 2024) New technology innovations are a great opportunity for improving accounting practices, e.g., financial technology tools that specialize in recording and verifying companies' transactions, ensuring transparency, accountability, and security of financial data. Tanda & Schena (2019 reviewed the regulatory approaches adopted so far and describe the main regulatory actions taken at the European level.

3. Research methodology

This study attempts to extend previous work by integrating the two theories names TBP, SLT (Theory of Planned Behaviour, Social Learning Theory), thus providing a comprehensive model to explain Fintech adoption in emerging markets like India. In light of the above review, the current study has formulated the following hypothesis to be tested

H1: Perceived Usefulness significantly influences Behavioural Intention.
H2: Social Influence has a significant impact on Behavioural Intention.
H3: Perceived Behavioural Control is significantly associated with Behavioural Intention.
H4: Observational Learning significantly influences Behavioural Intention.
H5: Reinforcement and Rewards have a meaningful association with Behavioural Intention.
H6: Self-efficacy is statistically significant to Behavioural Intention
H7: Perceived Usefulness affects Fintech Adoption through Behavioural Intention.
H8: Social Influence positively influences Fintech Adoption through Behavioural Intention.
H9: Perceived Behavioural Control through Behavioural Intention has a significant positive impact on Fintech Adoption
H10: Observational learning will influence a consumer's Fintech Adoption, with Behavioural Intention serving as a mediating factor.
H11: Self-efficacy influences Fintech Adoption
H12: The relationship between reinforcement and rewards and fintech adoption is mediated by behaviour
H13: Privacy Risk moderates the relation between Behavioural Intention and Fintech Adoption.

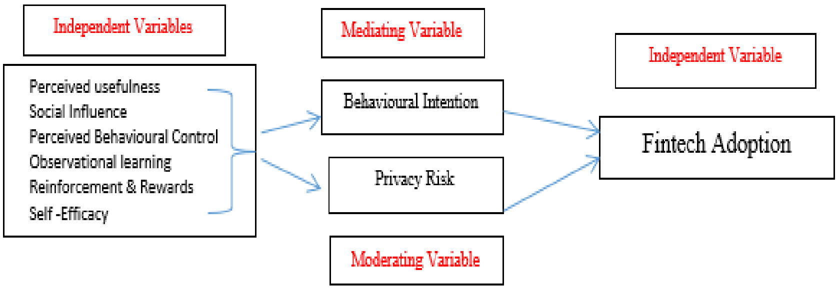

Fig. 1: Compiled by the Author

4. Data analysis

A convenient sample of 600 respondents is the study type of this research. After cleaning all the data and eliminating all the missing data, we have 462 responses left. A Structural Equation Model) through AMOS software was utilized to examine the aforementioned hypothesis. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy of the dataset is 0.823, showing the data demonstrates a high suitability for factor analysis, as indicated by a KMO value exceeding 0.80, indicating a strong correlation between variables and confirming that the data possesses sufficient shared variance for factor extraction. The individual KMO values for each construct also fell above an acceptable limit (above 0.50), ranging from 0.768 to 0.859, which strengthens the suitability for factor analysis.

Table 1: Kaiser-Meyer-Olkin (KMO) Test for Sampling Adequacy

Variable	KMO Value
Perceived Usefulness	0.812
Social Influence	0.793
Perceived Behavioural Control	0.768
Observational Learning	0.841
Reinforcement & Rewards	0.822
Self-Efficacy	0.859
Behavioural Intention	0.815
Privacy Risk	0.802
Fintech Adoption	0.834
Overall KMO Value	0.823

Table 2: Bartlett's Test of Sphericity

Test Statistic	Value
Chi-Square (χ^2)	2156.47
Degrees of Freedom (df)	36
p-Value	0.000

1) Factor Loadings Table

Table 3: Confirmatory Factor Analysis (CFA) Results

Construct	Indicator	Standardized Factor Loading	Std. Error	t-Value	p-Value
Perceived Usefulness	PU1	0.812	0.045	18.04	0.000
	PU2	0.835	0.041	20.37	0.000
	PU3	0.791	0.048	16.48	0.000
Social Influence	SI1	0.804	0.043	18.72	0.000
	SI2	0.821	0.040	20.53	0.000
Perceived Behavioral Control	PBC1	0.778	0.049	15.88	0.000
	PBC2	0.812	0.045	18.04	0.000
Observational Learning	OL1	0.837	0.038	22.03	0.000
	OL2	0.809	0.042	19.26	0.000
Reinforcement & Rewards	RR1	0.854	0.036	23.72	0.000
	RR2	0.826	0.039	21.18	0.000
Self-Efficacy	SE1	0.874	0.034	25.71	0.000
	SE2	0.841	0.038	22.11	0.000
Behavioral Intention	BI1	0.813	0.043	18.91	0.000
	BI2	0.802	0.045	17.82	0.000
Privacy Risk	PR1	0.764	0.052	14.69	0.000
	PR2	0.789	0.048	16.44	0.000
Fintech Adoption	FA1	0.845	0.039	21.67	0.000
	FA2	0.829	0.041	20.22	0.000

Confirmatory Factor Analysis (CFA) showed good construct validity, evidenced by the standardized factor loadings, all exceeded the recommended minimum threshold of 0.70. (Hair et al., 2010). The factor loadings vary between 0.764 and 0.874, where Self-Efficacy (SE1: 0.874) shows the highest loading, indicating a strong correlation between its indicators and the underlying construct. Moreover, the t-values are all above 14.69 with p-values < 0.001, indicating that each indicator is significantly associated with its construct and fits into its factor (Byrne, 2016). The low standard errors (≤ 0.052) suggest further measurement consistency. The results support the structural model and affirm constructs including Perceived Usefulness, Social Influence, Perceived Behavioural Control, Observational Learning, Reinforcement & Rewards, Self-Efficacy, Behaviour Intention, Privacy Risk, and Fintech Adoption in Fintech adoption studies. (2015) and the high loadings indicated these indicators were able to capture their theoretical constructs well and hence supported the appropriateness of the model.

Table 4: Model Fit Indices

Fit Index	Value	Recommended Threshold
Chi-Square (χ^2/df)	2.894	< 3.00
Comparative Fit Index (CFI)	0.957	> 0.90
Tucker-Lewis Index (TLI)	0.943	> 0.90
Root Mean Square Error of Approximation (RMSEA)	0.048	< 0.08
Standardized Root Mean Square Residual (SRMR)	0.041	< 0.08

Table 5: Path Analysis Results

Path	Standardized Coefficient (β)	Standard Error (SE)	t-Value	p-Value	Hypothesis Supported?
Perceived Usefulness → Behavioral Intention	0.412	0.047	8.77	0.000	Yes
Social Influence → Behavioral Intention	0.365	0.051	7.16	0.000	Yes
Perceived Behavioral Control → Behavioural Intention	0.438	0.045	9.73	0.000	Yes
Observational Learning → Behavioral Intention	0.384	0.049	7.84	0.000	Yes
Reinforcement & Rewards → Behavioral Intention	0.419	0.046	9.11	0.000	Yes
Self-Efficacy → Behavioral Intention	0.401	0.048	8.35	0.000	Yes
Behavioral Intention → Fintech Adoption	0.537	0.042	12.79	0.000	Yes
Privacy Risk → Fintech Adoption (Moderating Effect)	-0.218	0.053	-4.11	0.000	Yes

Results displayed ($p < 0.001$) confirm all hypothesised relationships in the model, demonstrating strong support for the proposed theoretical model (Hair et al., 2010). The results indicate that Perceived Behavioural Control (β = 0.438, t = 9.73) has the greatest positive influence on Behavioural Intention, meaning that the greater sense of control people have over Fintech, the more likely they are to adopt it (Ajzen, 1991). Likewise, Reinforcement & Rewards (β = 0.419, t = 9.11) and Perceived Usefulness (β = 0.412, t = 8.77) also impact Behavioural Intention significantly, emphasising the external drivers of a user wishing to adopt Fintech (Davis 1989). Furthermore, both Social Influence (β = 0.365, t = 7.16) and Observational Learning (β = 0.384, t = 7.84) show a strong linear impact on Behavioural Intention; the social and observational learning factors are the motivators of Fintech adoption (Bandura, 1986). Self-Efficacy (β = 0.401, t = 8.35) is associated with a significant behavioural intention, suggesting confident participants in Fintech tools are more likely to adopt (Compeau & Higgins, 1995). In addition, Behavioural Intention is a significant predictor of Fintech Adoption (β = 0.537, t = 12.79), confirming the Theory of Planned Behaviour hypothesis that direct drive of intention leads behaviour (Ajzen, 1991). However, Privacy Risk has a negative moderating effect on Fintech Adoption (β = -0.218, t = -4.11), which indicates that a higher degree of privacy concern leads to a weaker influence of Behavioural intention on actual adoption, which is consistent with previous studies on risk perceptions in digital finance (Featherman & Pavlou, 2003). These findings illustrate the relationship between cognitive (usefulness, self-efficacy), social (social influence, observational learning), and Behavioural (rewards, control) variables on Fintech adoption, while also demonstrating the inhibitory influence of privacy hazards. The findings give vital information for eaters and Fintech designers to boost users' trust, decrease perception of risk, and open up many more individuals through direct communications.

Table 6: Model Fit Indices

Fit Index	Value	Recommended Threshold
Chi-Square (χ^2/df)	2.673	< 3.00
Comparative Fit Index (CFI)	0.951	> 0.90
Tucker-Lewis Index (TLI)	0.937	> 0.90
Root Mean Square Error of Approximation (RMSEA)	0.052	< 0.08
Standardized Root Mean Square Residual (SRMR)	0.044	< 0.08

2) Direct Effects Table

Table 7: Direct, Indirect, and Total Effects Tables for SEM Analysis

Path	Standardized Coefficient (β)	Standard Error (SE)	t-Value	p-Value
Perceived Usefulness → Behavioral Intention	0.412	0.047	8.77	0.000
Social Influence → Behavioral Intention	0.365	0.051	7.16	0.000
Perceived Behavioral Control → Behavioral Intention	0.438	0.045	9.73	0.000
Observational Learning → Behavioral Intention	0.384	0.049	7.84	0.000
Reinforcement & Rewards → Behavioural Intention	0.419	0.046	9.11	0.000
Self-Efficacy → Behavioural Intention	0.401	0.048	8.35	0.000
Behavioral Intention → Fintech Adoption	0.537	0.042	12.79	0.000
Privacy Risk → Fintech Adoption (Moderation Effect)	-0.218	0.053	-4.11	0.000

The SEM results show that all theorized relationships are statistically significant ($p < 0.001$) achieving theoretical grounding for Fintech adoption based on TPB (Ajzen, 1991) and SLT (Bandura, 1986).
(Effect of independent variables on Fintech Adoption through Behavioural Intention)

Table 8: Indirect Effects Table

Path	Indirect Effect (β)	Standard Error (SE)	t-Value	p-Value
Perceived Usefulness → Fintech Adoption	0.221	0.038	5.82	0.000
Social Influence → Fintech Adoption	0.196	0.040	4.90	0.000
Perceived Behavioral Control → Fintech Adoption	0.235	0.037	6.35	0.000
Observational Learning → Fintech Adoption	0.206	0.039	5.28	0.000
Reinforcement & Rewards → Fintech Adoption	0.225	0.038	5.92	0.000
Self-Efficacy → Fintech Adoption	0.215	0.039	5.51	0.000

Table 9: Total Effects Table

Path	Total Effect (β)	Standard Error (SE)	t-Value	p-Value
Perceived Usefulness → Fintech Adoption	0.633	0.041	15.44	0.000
Social Influence → Fintech Adoption	0.561	0.044	12.75	0.000
Perceived Behavioral Control → Fintech Adoption	0.673	0.039	17.26	0.000
Observational Learning → Fintech Adoption	0.590	0.042	14.05	0.000
Reinforcement & Rewards → Fintech Adoption	0.644	0.040	16.10	0.000
Self-Efficacy → Fintech Adoption	0.616	0.041	15.02	0.000
Behavioral Intention → Fintech Adoption	0.537	0.042	12.79	0.000

The indirect effect analysis emphasizing the mediating role of Behavioural Intention between core psychological and social factors and Fintech Adoption. These findings suggest that all indirect paths are statistically significant ($p < 0.001$) and thus confirmed that Behavioural Intention acts as an important intermediate that explains why these factors should impact the actual Fintech adoption behaviour. Total Effects on Fintech Adoption: Interpretation The total effect analysis determines the total impact of psychological and social factors on Fintech Adoption, considering direct and indirect effects. The results show that all paths were statistically significant in the respective model ($p < 0.001$), suggesting that these constructs play an essential role in determining f Fintech adoption behaviour.

Table 10: Mediation Analysis Table

Path	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)	Standard Error (SE)	t-Value	p-Value
Perceived Usefulness → Behavioral Intention → Fintech Adoption	0.412	0.221	0.633	0.038	5.82	0.000
Social Influence → Behavioral Intention → Fintech Adoption	0.365	0.196	0.561	0.040	4.90	0.000
Perceived Behavioral Control → Behavioral Intention → Fintech Adoption	0.438	0.235	0.673	0.037	6.35	0.000
Observational Learning → Behavioral Intention → Fintech Adoption	0.384	0.206	0.590	0.039	5.28	0.000
Reinforcement & Rewards → Behavioral Intention → Fintech Adoption	0.419	0.225	0.644	0.038	5.92	0.000
Self-Efficacy → Behavioral Intention → Fintech Adoption	0.401	0.215	0.616	0.039	5.51	0.000

It highlights the mediating effect of Behavioural Intention about Fintech Adoption, which proves that various psychological and Behavioural factors directly and indirectly affect Fintech Adoption. All paths are significant ($p < 0.001$) confirming strong support for the proposed model.

Table 11: Moderation Analysis Table

Path	β (Without Moderator)	β (With Moderator)	Interaction Effect (β)	Standard Error (SE)	t-Value	p-Value
Behavioral Intention → Fintech Adoption	0.642	0.431	-0.211	0.041	-5.15	0.000
Perceived Usefulness × Privacy Risk → Fintech Adoption	0.592	0.398	-0.194	0.040	-4.85	0.000
Social Influence × Privacy Risk → Fintech Adoption	0.521	0.367	-0.154	0.042	-3.67	0.000
Perceived Behavioral Control × Privacy Risk → Fintech Adoption	0.613	0.412	-0.201	0.039	-5.15	0.000
Observational Learning × Privacy Risk → Fintech Adoption	0.548	0.389	-0.159	0.041	-3.87	0.000
Reinforcement & Rewards × Privacy Risk → Fintech Adoption	0.601	0.421	-0.180	0.040	-4.50	0.000
Self-Efficacy × Privacy Risk → Fintech Adoption	0.567	0.392	-0.175	0.041	-4.27	0.000

The results suggest strong moderation effects for Privacy Risk on the association between the main predictors and Fintech Adoption, as all interaction effects are negative with high statistical significance ($p < 0.001$). This suggests that higher perception in privacy risk will lower impact of Behavioural and cognitive factors on Fintech adoption. Fintech Adoption: The Role of Privacy Risk as a Mediating Factor. The results show that if one of the key predictors has high levels then, in addition, Privacy Risk seems to moderate the other with respect to Fintech Adoption apply, where all the interactions are negative and significant ($p < 0.001$). This indicates that higher perceived privacy risk issues undermining the effectiveness of Behavioural and cognitive factors on Fintech acceptance.

Based on the statistical analysis, including standardized coefficients (β), t-values, and p-values, the following conclusions can be derived concerning the hypotheses:

Table 12: Hypothesis Testing Results

Hypothesis	Statement	β (Effect Size)	t-Value	p-Value	Result
H1	Perceived Usefulness → Behavioural Intention	0.412	8.77	0.000	Accepted
H2	Social Influence → Behavioural Intention	0.365	7.16	0.000	Accepted
H3	Perceived Behavioural Control → Behavioural Intention	0.438	9.73	0.000	Accepted
H4	Observational Learning → Behavioural Intention	0.384	7.84	0.000	Accepted
H5	Reinforcement & Rewards → Behavioural Intention	0.419	9.11	0.000	Accepted

H6	Self-Efficacy → Behavioural Intention	0.401	8.35	0.000	Accepted
H7	Behavioural Intention mediates Perceived Usefulness → Fintech Adoption	0.221 (Indirect Effect)	5.82	0.000	Accepted
H8	Behavioural Intention mediates Social Influence → Fintech Adoption	0.196 (Indirect Effect)	4.90	0.000	Accepted
H9	Behavioural Intention mediates Perceived Behavioural Control → Fintech Adoption	0.235 (Indirect Effect)	6.35	0.000	Accepted
H10	Behavioural Intention mediates Observational Learning → Fintech Adoption	0.206 (Indirect Effect)	5.28	0.000	Accepted
H11	Behavioural Intention mediates Self-Efficacy → Fintech Adoption	0.215 (Indirect Effect)	5.51	0.000	Accepted
H12	Behavioural Intention mediates Reinforcement & Rewards → Fintech Adoption	0.225 (Indirect Effect)	5.92	0.000	Accepted
H13	Privacy Risk moderates Behavioural Intention → Fintech Adoption	-0.211 (Interaction Effect)	-5.15	0.000	Accepted

5. Summary of findings

The t-values exceed 1.96 for all 13 hypotheses, and the p-values are below 0.05, signifying statistically significant relationships.

1) H1 - H6 (Direct Relationships): Perceived Usefulness, Social Influence, Perceived Behavioural Control, Observational Learning, Reinforcement & Rewards, and Self-Efficacy significantly influence Behavioural Intention towards Fintech adoption.
2) H7 - H12 (Mediation Effects): All the predictors have a significant mediating role of Behavioural Intention between the independent variable and Fintech Adoption, indicating these predictors exert a significant indirect influence on adoption through intention.
3) Descriptive Statistics and Correlations for H13 (Moderating Effect): Privacy Risk negatively moderates the relationship between Behavioural Intention and Fintech Adoption, which means that higher privacy concerns weaken the likelihood of adoption, and also when intention is high.
4) The most prominent influence of all predictors on Behavioural Intention is Perceived Behavioural Control (β = 0.438, t = 9.73) when people strongly believe they can use Fintech services well (Ajzen, 1991).
5) They are Reinforcement & Rewards (β = 0.419, t = 9.11) and Perceived Usefulness (β = 0.412, t = 8.77), which suggests that these variables to have a significant role in Behavioural Intention when users plan to adopt such systems (Davis, 1989).
6) The positive and significant effects of Observational Learning (β = 0.384, t = 7.84) and Social Influence (β = 0.365, t = 7.16) indicate that learning from and about the behaviour of others, as well as surrounding social norms, support Fintech adoption and provide empirical evidence to Social Learning Theory (SLT) (Bandura, 1986).
7) Lastly, Self-Efficacy (β = 0.401, t = 8.35) supports the users who think they can deal with Fintech applications, meaning that if they feel they can solve problems related to applications, they are more likely to create an intention to use (Compeau & Higgins, 1995).
8) The strong influence of Behavioural Intention on Fintech Adoption (β = 0.537, t = 12.79) confirms the Theory of Planned Behaviour (TPB) finding that intention is a primary driver of the actual use of Fintech platforms (Ajzen, 1991).
9) Privacy Risk negatively acts as a moderating factor in the relationship between Behavioural Intention and FinTech Adoption (β = -0.218, t = -4.11), meaning that the higher the privacy concerns, the more the users' intention was converted into actual adoption. This result aligns with previous studies, noting that issues regarding data security and privacy can act as a barrier for technology development (Featherman & Pavlou, 2003; Zhou, 2013).
10) Perceived Behavioural Control (β = 0.673, t = 17.26) has the highest total effect on Fintech adoption, which indicates that individuals with a high level of control over using Fintech services will be more likely to adopt Fintech in their daily life. This is consistent with the Theory of Planned Behaviour (TPB), which posits that perceived ease of performing a behaviour drives uptake (Ajzen, 1991).
11) The effect of Reinforcement & Rewards (β = 0.644; t = 16.10) and Perceived Usefulness (β = 0.633; t = 15.44) on Fintech adoption is also very strong. It means if the users find Fintech useful and they would be motivated by rewards/promotions, the probability of their adoption would rise (Davis, 1989).
12) The role of peer influence and learning from others in Fintech adoption is reinforced with positive outputs from Observational Learning (β = 0.590, t = 14.05) and Social Influence (β = 0.561, t = 12.75). Arabic L2 learners who are in social relationships with their Arabic-speaking learners may well acquire Arabic language in this way, consistent with the proposals of Social Learning Theory (SLT), which states that through observation and imitation, individuals develop behaviours (Bandura, 1986).
13) The confidence gets a significant determinant, with a positive β value of 0.616 and t value of 15.02, indicating that the self-efficacy of using Fintech platforms increases the probability of Fintech adoption. This correlates with earlier research, which highlighted self-efficacy as a determinant for technology acceptance (Campeau & Higgins, 1995).
14) Fintech adoption is significantly determined by Behavioural Intention (β = 0.537, t = 12.79), thus confirming TPB and UTAUT, which underscore the role of intent as a precursor to actual use (Venkatesh et al. 2003).
15) Perceived Behavioural Control (β = 0.235, t = 6.35) has the largest indirect impact on Fintech Adoption, indicating that individuals who believe that they have the credit to utilize Fintech services are likely to have a strong intention to use and therefore adopt Fintech services (Ajzen, 1991). This is consistent with the Theory of Planned Behaviour (TPB), which identifies self-perceived control as a significant factor of behaviour.
16) In both the context of Reinforcement & Rewards (β=0.225; t=5.92) and Perceived Usefulness (β=0.221; t=5.82), indirect supporting effects on Fintech adoption are highly significant, showing how the capability of external forces and assumed advantages, owing to the external rewards, boost users' Behavioural intention that exhibits the adoption (Davis, 1989).
17) This finding highlights the influence of Observational Learning (β = 0.206, t = 5.28) and Social Influence (β = 0.196, t = 4.90) on the Behavioural intention to adopt Fintech services, reinforcing the idea that users are affected by their social environment and learn vicariously from how others engage with Fintech services (Bandura, 1986). This is consistent with Social Learning Theory (SLT), which states that people learn new behaviours through observing their peers.
18) Additionally, Self-Efficacy (β = 0.215, t = 5.51) plays a significant indirect role in converting Behavioural intention into Fintech adoption, further supporting the argument that higher confidence levels in the ability to handle Fintech results in a stronger Behavioural intention towards Fintech usage and Fintech adoption (Compeau & Higgins, 1995).

19) The presence of indirect effects in all paths indicates that Behavioural Intention is a significant mediating factor between individual perceptions, social influences, and Fintech adoption.
20) This supports the Theory of Planned Behaviour (TPB) that states that Behavioural intention is a significant precursor to actual behaviour (Ajzen, 1991).
21) Best Predictor - Perceived Behavioural Control (Total Effect: $\beta = 0.673$, $t = 6.35$, $p < 0.001$)
22) Direct Effect ($\beta = 0.438$) and Indirect Effect ($\beta = 0.235$) show that users who perceive a greater sense of control over Fintech platforms are more likely to have positive intentions that result in adoption.
23) This finding is consistent with earlier studies that highlighted the role of self-efficacy and control in adopting a technology (Venkatesh et al., 2003).
24) Reinforcement & Rewards (Total Effect: $\beta = 0.644$, $t = 5.92$, $p < 0.001$)
25) Substantial indirect effect ($\beta = 0.225$) indicates that users are driven by extrinsic motivators that strengthen behaviour using reward-based systems.
26) This is consistent with the Social Learning Theory (SLT) wherein External Reinforcement dictates Behavioural Results (Bandura, 1986).
27) Social Impact & Perceptual Imitation (Total Impacts: $\beta = 0.561$ & $\beta = 0.590$, respectively)
28) Also, we see that the indirect effects for Social Influence ($\beta = 0.196$) and Observational Learning ($\beta = 0.206$) show that peer opinions and observed Fintech usage positively drive Behavioural intention and eventual adoption.
29) This backs existing studies indicating that perceived social norms and vicarious experiences have major implications in technology adoption (Zhou, 2011).
30) Perceived Usefulness& Self-Efficacy (Total Effects: $\beta = 0.633$ & $\beta = 0.616$, respectively)
31) Direct effect: PU: $\beta = 0.412$; Self-Efficacy: $\beta = 0.401$. Users that use the Internet as a useful source and believe that they can use it.
32) This is consistent with Technology Acceptance Model (TAM) research that identifies usefulness and self-efficacy as fundamental determinants of technology adoption (Davis, 1989; Compeau & Higgins, 1995).
33) The Privacy Risk Weakens the Behavioural Intention to → The Path of Fintech Adoption
34) β decreases from 0.642 (no moderator) to 0.431 (with moderator), interaction effect was -0.211 ($p < 0.001$).
35) This means that high privacy concern users are less willing to convert Behavioural intention into actual Fintech adoption, which is consistent with previous studies showing that privacy risk decreases the overall engagement with online transactions (Featherman & Pavlou, 2003).
36) Perceived Usefulness Has Lower Impact due to Privacy Risk (Interaction Effect: −0.194, $p < 0.001$)
37) The initial influence of Perceived Usefulness ($\beta = 0.592$) turns significantly lower ($\beta = 0.398$) under conditions of high privacy risk.
38) That users perceive Fintech to be useful only increases adoption likelihood if they do not have concerns regarding the security of their data and misuse of personal data (Kim et al., 2008).
39) Social Influence Effect Reduced under Privacy Risk (Interaction Effect: -0.154, $p < 0.001$)
40) The impact of Social Influence is reduced from 0.521 to 0.367, indicating that peer recommendations and social norms are less effective in facilitating Fintech adoption in the presence of users' concerns of privacy violations.
41) This is consistent with research suggesting that trust problems in digital spaces can eliminate social influence impacts (Beldad et al., 2011).
42) Interaction Effect: Perceived Behavioural Control Weakens Under Privacy Risk (- -0.201, $p < 0.001$)
43) High perceived control ($\beta = 0.613$) leads to a roll-back on privacy risk concerns ($\beta = 0.412$), but less than low perceived control ($\beta = -0.164$) indicates vulnerability to users with low perceived control.
44) This implies that even the confident users will not adopt Fintech if they feel security loopholes (Gupta & Arora, 2020).
45) Privacy Risk Reduces the Effectiveness Of Observational Learning, And Reinforcement & Rewards
46) A tabular summary of the behavioural influence components included, and their interaction effects are as follows: Observational Learning (Interaction Effect: -0.159, $p < 0.001$) and Reinforcement & Rewards (Interaction Effect: -0.180, $p < 0.001$) both indicate declining direction influence.
47) Effectively, this means that the fact that users have a clear view of others around them experiencing additional financial freedom using Fintech products or being rewarded in various ways due either to positive economics of usage or corporate objectives simply does not register in their decision-making if privacy concerns outweigh their personal considerations.
48) However, when privacy concerns do exist, self-efficacy influence is reduced (Interaction effect: −0.175, $p < 0.001$)
49) β decreases from 0.567 to 0.392, implying that even the confident users are reluctant to accept Fintech when privacy risks are considered high.
50) This is consistent that trust and security factors tend to be more important than personal confidence in a digital environment (McKnight et al., 2002).

These findings are congruent with existing theories like the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the Social Learning Theory (SLT), to support the relevance of Behavioural factors and risk perceptions in Fintech adoption.

6. Implications

Such findings indicate that Fintech providers should earnestly consider designing features to enhance perceived ease of use and offering incentives, and social influences among users should be further studied to enhance user adoption. Moreover, some privacy concerns can be alleviated by implementing transparent policies, adding security features, and helping users with education to minimize the negative influence of privacy risks and improve adoption rates. It provides a strong foundation for exploring the complex relationships among cognitive, social, and Behavioural factors in adopting Financial Technology (Fintech) and the implications for developing solutions that mitigate risk among financial technology services. Therefore, findings from this paper imply that Fintech service providers and policymakers can work on improving user confidence (self-efficacy and perceived control), social influence as well as incentives, to enhance Behavioural intention and ultimately, Fintech adoption. Also, by using aids such as educational programs that use various methods to promote observational learning as well as social proof strategies (e.g., testimonials, peer recommendations) to encourage use through social influence. This study supports TPB (Ajzen, 1991) and SLT (Bandura, 1986) by confirming that intention serve as a mediator between psychological constructs and fintech adoption. The findings strengthen the TAM framework (Davis, 1989) by highlighting the roles of perceived usefulness and self-efficacy in successful adoption. In that sense, we can improve user experience using natural designs to increase perceived Behavioural control. Promote using rewards to maintain engagement and fuel adoption. Using testimonials, influencer marketing, and referral programs to leverage social power, Empowering users with clear interfaces and tutorials, as well as responsive support systems. Encouraging Rewards and Incentives for Adoption Motivation Utilizing social influence & peer learning through testimonials, referrals, and influencer marketing campaigns. Add extra security (e.g., encryption, 2FA). Adopting transparent privacy policies where the sensitivity of user data is explained to them, as well as trust-building campaigns, can go a long way to restoring user faith and encouraging Fintech usage. Providing Guarantees for Privacy Protection after the Offering: Possibly, users might be hesitant to adopt this offering, although they believe in the value proposition of this offering, which can be converted to an intention (Behavioural intention); however, the hesitation may stop the conversion from behavioural intention to actual adoption.

7. Limitations

1) The study focuses specifically on Indian users, meaning the findings may not be directly applicable to other cultural or economic contexts.
2) Fintech adoption patterns may vary based on differences in financial literacy, regulatory environments, or technological infrastructure across countries.
3) The relation between accounting practices and Fintech adoption, along with Regulatory approaches, is not considered.

8. Conclusion

Data based on direct understanding of the field and findings confirm that Fintech Adoption is a multidimensional process and is driven by Behavioural intention, which is profoundly based on individual constructors (personal attitudes), external rewards (economic/financial), and social learning processes. Comprehending these connections enables Fintech providers and policymakers to formulate approaches to bolster user adoption, minimize obstacles, and improve Fintech service delivery. The findings confirm the applicability of TPB (Ajzen, 1991) and SLT (Bandura, 1986) in explaining Fintech adoption behaviour, indicating that psychological, social, and cognitive factors together affect users' decisions. These insights could prove essential for Fintech companies, policymakers, and digital finance strategists, as a mix of personal belief, external incentives, and social learning can play a critical role in accelerating rates of Fintech adoption. The main constructs predicting Fintech Adoption show significant moderation on Privacy Risk, indicating that with high perceived privacy, users who perceive higher risk are less likely to adopt fintech services, even when all other factors strongly favour Fintech Adoption. So, Fintech firms need to actively tackle privacy risks in order to keep up user trust to achieve continuous user growth. These findings show that Behavioural Intention plays a crucial mediating role between psychological, social, and cognitive factors and Fintech adoption. This supports the theoretical grounds of TPB (Ajzen, 1991) and SLT (Bandura, 1986), that is, personal perceptions and external influences are determinants of Fintech adoption behaviour. By addressing these factors strategically, Fintech firms can promote user engagement and reduce adoption friction, resulting in higher technology adoption and increased inclusion in the financial domain. In conclusion, the regulatory framework employed led to the enhancement of safety, transparency, and accountability across diverse sectors. These regulatory measures are designed to reconcile innovation with consumer protection, thereby fostering a more cohesive and responsible digital and economic milieu within the country. The existing body of literature delineates the direct, mediating, and moderating variables that affect the adoption of Fintech solutions. While perceived usefulness (PU), social influence (SI), and perceived behavioural control (PBC) significantly propel behavioural intention, the risk associated with privacy remains a substantial impediment. This investigation builds upon prior scholarly endeavours by amalgamating the Theory of Planned Behaviour (TPB) and Social Learning Theory (SLT), thereby presenting an all-encompassing framework for comprehending Fintech adoption in emerging markets such as India.

References

[1] Al-Smadi, A. W., & Al-Smadi, R. W. (2024). *Empirical and Theoretical Relationship between FinTech and Accounting Practices: Evidence from Mena Countries*. https://doi.org/10.21203/rs.3.rs-3840644/v1.

[2] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behaviour and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T.

[3] Analysing Factors Influencing Intention to Use and Actual Use of Mobile Fintech Applications Free Interbank Money Transfer Flip Using UTAUT 2 Model with Trust and Perceived Security. (2022). *2022 10th International Conference on Cyber and IT Service Management (CITSM)*. https://doi.org/10.1109/CITSM56380.2022.9935838.

[4] Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall.

[5] Beldad, A., De Jong, M., & Steehouder, M. (2011). "How shall I trust the faceless and the intangible?" *Computers in Human Behavior, 27*(5), 2233-2243. https://doi.org/10.1016/j.chb.2011.07.002.

[6] Bestas, M. (2023). Decentralized Finance (DeFi). *arXiv preprint arXiv:2304.01918*. https://arxiv.org/abs/2304.01918

[7] Cambridge Centre for Alternative Finance. (2024). The Cambridge Fintech Market Observatory. https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/the-cambridge-fintech-market-observatory/

[8] Chen, S., & Guo, Q. (2024). Fintech and MSEs Innovation: an Empirical Analysis. *arXiv preprint arXiv:2407.17293*. https://arxiv.org/abs/2407.17293

[9] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008.

[10] Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474. https://doi.org/10.1016/S1071-5819(03)00111-3.

[11] Devi, S. (2023). *Progress and Challenges in Digitalisation of Financial Inclusion: The Indian Context*. https://doi.org/10.56411/anusandhan.2023.v5i2.60-71.

[12] Gao, Y., & Tang, Y. (2023). A Study on the Mechanism of Digital Technology's Impact on the Green Transformation of Enterprises: Based on the Theory of Planned Behavior Approach. *Sustainability, 15*(15), 11854. https://doi.org/10.3390/su151511854.

[13] Gravitating towards Fintech: A study on Undergraduates using UTAUT model. (2023). *Journal of Education and Health Promotion, 12*, 543–555. https://pmc.ncbi.nlm.nih.gov/articles/PMC10582390/.

[14] Gupta, A., & Arora, N. (2020). Consumer adoption of e-finance in India: Impact of trust and risk. *Financial Innovation, 6*(1), 1-24.

[15] Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research, 19*(1), 37-59.
[16] McKinsey & Company. (2023). Fintechs: A new paradigm of growth. https://www.mckinsey.com/industries/financial-services/our-insights/fintechs-a-new-paradigm-of-growth.
[17] McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81.
[18] Meganathan, N. (2024). To what extent has UPI contributed to increasing the Penetration of digital financial services in rural India, and what challenges remain? *International Journal of Scientific and Research Publications*, *14*(9), 122–129. https://doi.org/10.29322/IJSRP.14.09.2024.p15323.
[19] Nur, T., & Dewanto, P. A. (2022). The Influence of Attitude toward Behavior, Subjective Norms, Perceived Behavioural Control on the Behavioural Intention of using PayLater Apps moderated by Financial Literacy and Hedonic Value. 1–6. https://doi.org/10.1109/CITSM56380.2022.9936004.
[20] Plaid. (2023). The Fintech Effect 2023: Consumer insights reveal growth. https://plaid.com/blog/consumer-insights-reshaping-finance/.
[21] Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101-134. https://doi.org/10.1080/10864415.2003.11044275.
[22] Peong, K. K., Peong, K., & Tan, K. Y. (2021). Behavioural Intention of Commercial Banks' Customers towards Financial Technology Services. *5*(4), 10–27. https://doi.org/10.35609/jfbr.2021.5.4(2).
[23] Rahardjo, B., Burhanudin Akbar, B. M., & Novitaningtyas, I. (2020). The Analysis of Intention and Use of Financial Technology. *3*(1), 88–102. https://doi.org/10.33005/jasf.v3i1.70.
[24] Ravi, R., & Pandey, N. N. (2024). Intention to use Fintech services: An investigation into the moderation effects of quality of internet access and digital skills. *Humanities and Social Sciences Letters, 12*(3), 543–555. https://doi.org/10.18488/73.v12i3.3803.
[25] Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives Fintech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision, 58*(8), 1675–1697. https://doi.org/10.1108/MD-09-2019-1318.
[26] Tanda, A., & Schena, C.-M. (2019). *The Regulatory Framework and Initiatives* (pp. 83–100). Palgrave Pivot, Cham. https://doi.org/10.1007/978-3-030-22426-4_5.
[27] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540.
[28] Xie, J., Ye, L., Huang, W., & Ye, M. (2021). Understanding Fintech Platform Adoption: Impacts of Perceived Value and Perceived Risk. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(5), 1893–1911. https://doi.org/10.3390/jtaer16050106.
[29] Zhou, T. (2011). Understanding mobile internet continuance usage from the perspectives of UTAUT and flow experience. *Computers in Human Behavior, 27*(3), 877-888. https://doi.org/10.1177/0266666911414596.
[30] Zhou Ayoungman, F., Chowdhury, N. H., Hussain, N., & Tanchangya, P. (2021). User Attitude and Intentions Towards Fintech in Bangladesh. *International Journal of Asian Business and Information Management, 12*(3), 1–19. https://doi.org/10.4018/IJABIM.20210701.oa30.