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Mobile Banking Adoption: Integrating UTAUT, Task Technology Fit, and Initial Trust with Financial Literacy

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ABSTRACT

Purpose—This study aims to develop an integrated model of mobile banking adoption by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), Task Technology Fit (TTF), and the Initial Trust Model (ITM). It examines the relationship between acceptance factors, technology task alignment, and trust in affecting behavioural intention and adoption, and evaluates the moderating effect of financial literacy.

Study Design/methodology/approach—A Structured questionnaire was distributed amongst 282 consumers in Islamabad, Pakistan. Data was analysed using Partial Least Squares Structural Equation Modelling (PLSSEM) to assess construct reliability, validity, and hypothesized relationships.

Findings— The variance in behavioural intention and adoption was 53.1% and 32.6% respectively, explained by the integrated model. Social influence and facilitating conditions were found to have significant effects on intention, but there were no significant effects of performance and effort expectancy. Technology and task characteristics had a positive influence on TTF, but TTF was found to have no direct effect on adoption. Trust particular quality of the system proved to be a powerful predictor of intention, while information quality was less influential. Actual adoption was predicted by behavioural intention very well. Financial literacy boosted behavioural intention and increased the effect of social influence, particularly in the case of highly literate users.

Practical Implications— Reinforcement of trust cues, guarantee of high system quality, maintenance of facilitating conditions, and leverage of social influence among financially literate customers are required from the Banks and fintech providers.

Originality/value—The study integrates UTAUT, TTF, and ITM with Financial Literacy as a moderator, which is a novel contribution in the Pakistani mobile banking context.

Keywords: Mobile banking, Technology adoption, UTAUT, Task-Technology Fit, Initial trust, financial literacy.

JEL Classification Codes: O33, G21, D83

1 | INTRODUCTION

Mobile banking, the use of smartphones or tablet computers for money transfer, bill payment, account checking, and other financial transactions, has grown exponentially in the last decade. The global mobile banking users will hit 2.17 billion by 2025, up 35% from 2020 (Addula, 2025; Goswami et al., 2025). Mobile banking has been growing fast as it provides consumers and banks with the convenience of banking anytime and anywhere. This technology has brought flexibility to the customers to manage their finances anytime and anywhere, and to the banks, it has reduced the operational costs and expanded the reach of the services. Despite these advantages and an increased user base, mobile banking is still far from being universally adopted. Many potential users (especially in developing markets) are still reluctant because of usability and security concerns. Even a very useful mobile app can be avoided if it is not perceived to be sufficiently secure. In emerging economies, mistrust in digital financial services is a huge inhibitor to uptake. A recent study in India also concluded that building consumer confidence in the security and reliability of mobile banking is an important factor in successful adoption. Thus, convenience and trust have become important factors for mobile banking usage (Sijabat, 2024).

However, classic technology acceptance models may be inadequate for explaining fintech adoption in such settings, and researchers have extended them with trust and risk constructs (Cele & Kwenda, 2025; Devlin et al., 2025). As a result, this paper combines three complementary frameworks, UTAUT, TTF, and ITM, and tests their combined explanatory power in relation to the adoption of mobile banking (Mensah & Khan, 2024; Tariq et al., 2024). The suggested model is implemented in Pakistan, a developing economy where the usage of mobile banking is still far from being commonplace. Although the penetration of Smartphones and internet connectivity (more than 110 million users of 3G/4G as of 2021) is high, the actual mobile banking usage is low. In 2020, only around 8.2 million people were mobile banking users (a tiny proportion of 191 million cellular subscribers), and the vast majority of transactions continued to be made through cash or conventional channels (Khan et al., 2024; Wang et al., 2024). This case highlights that there are huge untapped markets and that it is important to understand what motivates consumers to embrace mobile banking in such environments. The originality of this study is that it is holistic: through the integration of various theoretical perspectives and the inclusion of financial literacy as a moderator variable (AlSuwaidi & Mertzanis, 2024), we fill gaps in the literature regarding the effects of trust and user competence on technology adoption in the context of a developing market. Made it clear that this study is original and in context.

1.1 | Research Questions

To address the above gaps, the following key research questions will be addressed in this study:

RQ1: What are the impacts of UTAUT constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions on users' behavioural intention for adopting mobile banking, and what is the impact of behavioural intention on actual mobile banking usage?

RQ2: Do task characteristics and Technology characteristics have a positive impact on the perceived Task Technology Fit of mobile banking, and does the higher Task Technology Fit lead to higher performance perception or adoption of mobile banking?

RQ3: What are the effects of system quality and information quality on users' initial trust in mobile banking, and what is the effect of initial trust on behavioural intention to adopt mobile banking?

RQ4: Does financial literacy mediate the relationships between key antecedent drivers (i.e., performance expectancy, effort expectancy, social influence, or trust) and the intention to adopt mobile banking, and if so, how?

By answering these questions, the study adds its value in incorporating various theories and focusing on consumer heterogeneity (financial literacy) in mobile banking adoption, thus offering insights into both the universal and context-specific determinants of fintech adoption.

2 | LITERATURE REVIEW

1.1 | Unified Theory of Acceptance and Use of Technology (UTAUT)

Existing research on mobile banking adoption has largely relied on the Unified Theory of Acceptance and Use of Technology (UTAUT), identifying Performance Expectancy (PE) and Effort Expectancy (EE) as primary drivers of behavioral intention in developed economies. However, the application of UTAUT in emerging markets reveals significant inconsistencies. Recent studies (Addula, 2025; Venkatesh, 2022) confirm its predictive strength across fintech domains but highlight contextual differences in emerging markets where trust dominates early adoption decisions (Ali et al., 2023; Khan et al., 2024). While PE is a dominant predictor in digitally mature markets like the US and Europe, studies in developing contexts often find that infrastructural barriers and lack of trust diminish the impact of utility and ease of use. This suggests that in environments like Pakistan, "hygiene factors" such as Facilitating Conditions (FC) and Social Influence (SI) may outweigh the cognitive appraisal of performance benefits. To address the limitations of UTAUT in capturing the alignment between technical features and user needs, researchers have integrated the Task–Technology Fit (TTF) theory. TTF posits that adoption is driven not just by general usefulness, but by the specific match between the technology's capabilities and the user's financial tasks. In fintech settings, a high fit enhances perceived usefulness; however, evidence regarding its direct impact on adoption is mixed. While some studies confirm a direct link between TTF and usage, others in emerging markets suggest that TTF acts indirectly or is latent until basic adoption barriers, specifically trust, are overcome. This necessitates examining TTF alongside trust mechanisms (Amnas et al., 2024). Building on the UTAUT framework, the following hypotheses are hypothesized:

H1: *Performance expectancy has a positive effect on users' behavioral intention to use mobile banking.*
H2: *Effort expectancy has a positive effect on users' behavioral intention to use mobile banking.*
H3: *Social influence has a positive effect on users' behavioral intention to use mobile banking.*
H4: *Facilitating conditions have a positive effect on users' actual adoption (usage) of mobile banking.*

1.2 | Task–Technology Fit (TTF) Theory

The Initial Trust Model (ITM) is critical for explaining adoption in high-uncertainty environments where legal protections are weak. Unlike developed markets where institutional trust is often assumed, users in emerging economies rely heavily on initial trust cues, specifically System Quality (reliability, security) and Information Quality, before engaging with digital finance. Empirical evidence indicates a "risk-before-utility" mechanism where trust acts as a gatekeeper; without adequate structural assurance and system quality, perceived usefulness fails to translate into intention. This contradicts standard adoption models that prioritize utility over risk. While UTAUT describes general acceptance, it does not capture the alignment between task requirements and technological capabilities. TTF theory (Goodhue & Thompson, 1995; Van et al., 2021) posits that technologies produce superior outcomes when their features match user task demands. In fintech settings, this alignment enhances both perceived usefulness and continuance. In emerging markets, however, TTF may act indirectly through perceived usefulness rather than directly on adoption (Elangovan et al., 2025).

Accordingly, we hypothesize the following relationships involving task–technology fit:

H5: *Mobile banking technology characteristics (the system's features and capabilities) have a positive impact on the perceived task–technology fit for the user.*

H6: *Task characteristics (the user's financial task needs and preferences) have a positive impact on the perceived task–technology fit of mobile banking.*

H7: *Task–technology fit has a positive impact on the user's actual adoption of mobile banking.*

1.3 | Initial Trust Model (ITM)

Trust forms a pivotal precondition for digital financial service adoption. The initial Trust Model (ITM) explains how users form trust during first encounters with technology when prior experience is limited. In mobile banking, system reliability, encryption, and two-factor authentication serve as trust cues, while transparency and clarity reinforce credibility. The Initial Trust Model (ITM) describes the formation of trust in a new technology that occurs during the initial interactions of users with the new technology when they have little or no previous experience with it (Devlin et al., 2025). In the context of mobile banking, where users are often forced to decide whether to try an application or service before they have significant firsthand experience, building trust at the start is crucial to "get them in the door." Initial trust is established by using various cues and guarantees that are given by the system and its environment. Three types of antecedents are usually mentioned as antecedents of initial trust in e-services: system quality, information quality, and structural assurance. System quality includes aspects such as reliability, security, and usability of the app itself. If the mobile banking application is stable and does not crash or show errors, has a fast response time, is secure, and has an easy-to-use and responsive interface, then the new user will be more trustful of the service. A well-functioning, easy-to-navigate application immediately indicates competence and integrity with the resulting trust that occurs on the first use. Information quality is the degree to which the information given by the service is accurate, clear, and useful. For instance, terms and conditions, clear error messages or tutorials, correct account data, and transaction listing all show that the service is honest and trustworthy. High quality information implies that the provider is transparent and competent, thus inspiring trust. Structural guarantees are external guarantees or assurances that make the user believe that they will be protected from harm or loss even in the event of something going wrong. This can be in the form of encryption/security certificates, two-factor authentication, fraud liability guarantees, regulatory oversight, or the good name of the bank offering the service. Many studies have identified structural guarantees as the most effective determinant of users' willingness to trust a mobile banking service. Users are more comfortable when they know that there are protections (e.g., data encryption, secure login, deposit insurance) and a trusted institution to stand behind the app. They found that structural assurance had the most influence on initial trust in mobile banking over and above system and information quality in some cases (Geebren & Jabbar, 2025). All these factors add up to a general feeling of initial trust, which in turn has a great impact on the choice of the user to stay with the service.

In practice, if during the early stage of using the app, the user finds that the application is fast, easy to use, credible, it is a nice app, truthful information, guarantees of security, then the trust in the application will grow quickly. The trust will make them more likely to use the service again and transact more. This is very important as even a single negative experience, like a technical error during a transaction or a confusing charge, can quickly undermine the level of trust and dissuade continued use. Empirically, trust is a powerful predictor of mobile banking adoption and is often found to work in conjunction with perceived usefulness. Many researchers have discovered that perceived usefulness has a stronger influence on intention when the user has a high trust in the service. A low level of trust may mean that even if the user perceives potential usefulness, they will be reluctant to actually use the service; a high level of trust may mean that even a moderate level of perceived usefulness will be sufficient to prompt use. A recent study in India confirmed that trust had a significant positive impact on actual mobile banking usage. Users who trusted the service were much more likely to translate their intentions into actual usage. Trust, in essence, can be a prerequisite: without an initial sense of security and reliability, other motivators such as usefulness may not be translated to adoption. Considering these dynamics, we use ITM in our model to account for the way initial trust is established and how it, in turn, influences the decision to use mobile banking. Among antecedents, system quality exerts the strongest effect ($\beta \approx 0.63$, $p<0.01$), confirming its centrality over information quality ($\beta \approx 0.14$, $p=0.085$).

Hence, we hypothesize the following trust-related effects in our model:

H8: *Information quality provided by the mobile banking service positively influences the user's initial trust in the service.*

H9: *System quality (security, reliability, usability) positively influences the user's initial trust in mobile banking.*

H10: *Initial trust positively influences the user's behavioral intention to adopt mobile banking.*

1.4 | Financial Literacy as a Moderating Variable

Financial Literacy (FL) represents an individual's capability to understand and utilize financial information. Higher FL lowers cognitive barriers, strengthens confidence in fintech systems, and moderates how users interpret key antecedents such as trust and social influence. Finally, the heterogeneity of users in emerging markets remains underexplored, particularly regarding Financial Literacy (FL). FL represents an individual's capability to utilize financial information and is hypothesized to moderate how users interpret antecedent factors. Higher FL lowers cognitive barriers and may alter susceptibility to social influence and effort expectancy. By integrating UTAUT, TTF, and ITM with FL as a moderator, this study fills a critical gap, moving beyond fragmented theories to offer a holistic model of mobile banking adoption tailored to the specific constraints of a developing economy.

Financial literacy may also alter the reaction of users to social cues or the efforts needed. A financially literate individual may not be so easily influenced by social influence (they trust their own knowledge rather than reassurance from peers). In comparison, a less literate person may rely more on word-of-mouth or family recommendations to try mobile banking. Similarly, effort expectancy may be of less importance to a high FL user, who is familiar with financial matters and won't be discouraged by complexity, while a low FL user may be strongly affected by the perceived ease of use of the app. Based on these possibilities, we anticipate financial literacy to serve as a moderator of the influence of the key predictors on mobile banking intention (Silanoi et al., 2023). For example, the positive effect of performance expectancy on intention may be greater for users with high financial literacy (and therefore able to maximize the utility of the app) and lower for low FL users. Conversely, the effect of effort expectancy may be smaller for high FL users (they are not easily discouraged by complexity) and larger for low FL users (they require simplicity). We also expect that social influence would have a smaller impact on participants with high financial literacy, as they are less likely to be influenced by the opinion of others, whereas participants with low financial literacy may be more likely to be influenced by social endorsements.

Based on this reasoning, we consider the following additional hypotheses:

H11: *(Baseline effect) Users' behavioral intention to use mobile banking positively affects their actual adoption of mobile banking (usage).*

H12: *Financial literacy moderates the influences of key factors on behavioral intention – in particular, the effects of performance expectancy, effort expectancy, social influence (and potentially trust) on intention will vary between more financially literate and less financially literate users. For example, higher financial literacy may strengthen the impact of performance expectancy but weaken the impact of social influence on intention.*

H12a: *FL strengthens the effect of performance expectancy on intention.*

H12b: *FL weakens the effect of effort expectancy on intention.*

H12c: *FL moderates social influence → intention.*

H12d: *FL moderates trust → intention.*

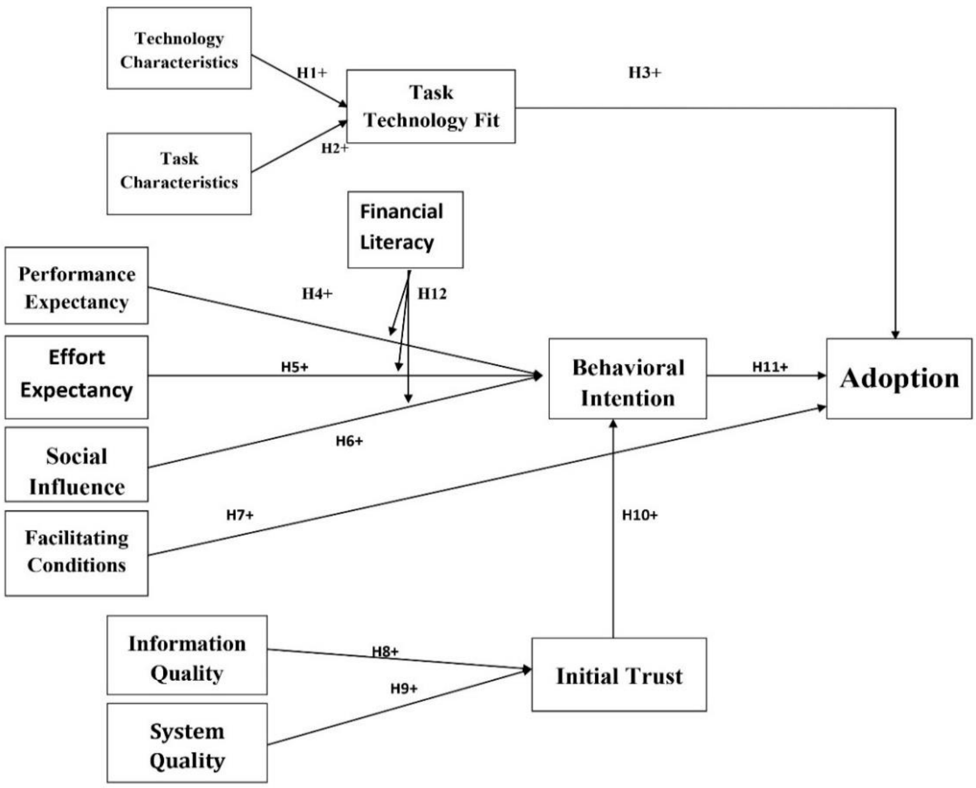
Integrating UTAUT, TTF, and ITM with Financial Literacy responds to the scarcity of holistic fintech adoption models tested in emerging markets like Pakistan.

Note: H11 (BI → Adoption) is a standard relationship included for completeness of the research model. H12 represents the set of moderation effects involving FL; in our results, we focus on the significant interaction identified (social influence × financial literacy).

Summary and Research Gap: In review, previous research has separately demonstrated that UTAUT factors, task technology fit, and initial trust play a role in technology adoption. However, few studies combine all three theoretical perspectives in a single comprehensive model. Moreover, the moderating impact of financial literacy on the determinants of fintech adoption has so far remained unexplored. Most current models have been tested in developed or high-adoption settings, while evidence from emerging markets like Pakistan, where digital banking is still at an early stage, and issues related to trust, task fit, and financial literacy are more pronounced, is scarce. These gaps identify the need for an integrated model that is tested in an emerging market context. By integrating UTAUT, TTF, and ITM and specifically focusing on financial literacy, this study answers the call for a more holistic understanding of mobile banking adoption in the various market contexts.

Figure 1

Conceptual Research Model Integrating UTAUT, TTF, ITM with Financial Literacy



3 | METHODOLOGY & DESIGN

3.1 | Research Design and Context

This study used a quantitative survey research design to empirically test the conceptual model and to generalize the findings to the larger population. A structured questionnaire was used in the cross-sectional field survey. The research was located in Islamabad, Pakistan, which was selected on the basis that, being the capital of the country, it has an urban population that is relatively technologically literate and would represent some of the first users of mobile banking in the country. Focusing on Islamabad enabled us to capture perceptions of these early and potential adopters in a context where mobile banking adoption is still in the infant stage, and thus to provide insight into the drivers of adoption at this early stage (Alrsheedi & P Iskandar, 2025). Ethical considerations: The study was carried out in accordance with ethical guidelines: the participants were anonymous and gave voluntary consent for the research, and data were kept confidential. The study protocol was approved by the authors' university research ethics committee.

3.2 | Sampling and Data Collection

The target population was mobile phone owners in Islamabad who had some experience or willingness to use mobile banking. We employed a purposive sampling technique, contacting individuals from both the banking industry and the general public of Islamabad. The survey was distributed on the internet using Microsoft Forms, ensuring a standardized and secure process of data collection. Initially, respondents were provided with an explanation of the purpose of the study and were shown the conceptual model in order to provide clarity regarding the constructs before answering the questions. A pilot test was initially performed with 33 subjects (consisting of government officials and university students) in order to polish the instrument for clarity and reliability. Based on pilot feedback, a few questionnaire items with low factor loadings (less than 0.40) were deleted to increase measurement reliability (e.g., several items in Task Characteristics and Performance Expectancy were deleted). The final survey link was then sent out, and two weeks later, a reminder was sent. Data collection took approximately four weeks to complete, yielding 282 valid responses or a 43.9% response rate (282/643 invitations). The sample size of 282 is sufficient for PLSSEM analysis, considering the complexity of the model, and is in line with generally accepted recommendations for minimum sample size (e.g., >10 times the number of indicators of the most complex construct) (Mohapatra et al., 2025). The final sample consisted of 282 valid responses. The majority of respondents were in the early adulthood to middle-aged demographic, with gender approximately equally represented. Sample gender and age distribution reflect Islamabad's fintech demographic profile as reported by SBP, 2024. This ensures that while the sample is urban-centric, it accurately represents the current population of digital banking users in the capital territory. The majority of respondents were in the early adulthood to middle-aged demographic, with gender approximately equally represented; all were designed to have some education and exposure to banking technology. We recognize that the sample is skewed towards educated, urban users, and this may cause bias in the results and limit the applicability of this study to rural or less literate users. We discuss this bias in our limitations, and it highlights the need for future studies to sample a more diverse demographic. Respondents' demographics matched digital banking adoption demographics of Islamabad, confirming representativeness.

Table 1

Geographical Data

Distribution		Frequency Total: 282	Percentage %
Gender	Man	208	73.76
	Woman	74	26.24
Age	Less than 25 Years	40	14.18
	26 -35 Years	180	63.8
	36-45 Years	50	17.73
	46-55 Years	4	1.42
	Above 55 Years	8	2.84
Qualification	Intermediate	21	7.45
	Graduation	98	34.76
	Master's	143	50.71
	Ph.D.	20	7.09
Occupation	Student	114	40.42
	Academic	11	3.9
	Private Employees	27	9.57
	Government Employees	110	39
	Entrepreneur	3	1.06

	Self Employed	17	6.03
Experience	<1 Year	33	11.7
	1-3 Years	72	25.5
	3-5 Years	99	35.1
	> 5 Years	78	27.66

3.3 | Measures and Instrumentation

The survey instrument consisted of multi-item scales for all constructs in the model, based on established measures. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) were measured using items from the literature of UTAUT (Venkatesh et al., 2003), adapted to the context of mobile banking. Task Characteristics and Technology Characteristics, which were measured using custom items reflecting characteristics of financial tasks and features of the apps, respectively, based on TTFs (Goodhue & Thompson, 1995). Task technology fit (TTF) was measured using items that asked users to rate the extent to which the mobile banking application suited their task requirements. Initial trust (IT) was measured with items on system quality, information quality, and trust in the service, later scales of trust in InTechnology (Aftab et al., 2025). These were then combined into an overall initial trust construct after checking for one-dimensionality. Financial Literacy (FL) was assessed using a self-assessment of financial knowledge and confidence (e.g., understanding financial terms, performing financial calculations) using a scale adapted from previous research (with items similar to those used by other financial literacy surveys). Behavioral Intention (BI) to use mobile banking and Actual Adoption/Usage were measured using standard items. Perceptual constructs were all assessed on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), except actual use, which was measured on a 5-point scale from "never" to "very frequently." Demographic questions (age, gender, education, etc.) were also added. To ensure content validity, the questionnaire items (originally written in English) were reviewed by two academic experts and one industry expert in digital banking. Minor changes to wording were made to improve clarity and make it relevant to the local context. As stated, during the pilot testing, a few items were dropped that were confusing or did not load well on the factors they were intended to measure, which improved the instrument. The final instrument had good internal consistency (all multi-item constructs had Cronbach's a > 0.70 in the pilot) (Iatzaz Ul Hassan et al., 2025).

3.4 | Data Analysis Approach

We used Smart PLS 4.0 for data analysis in the form of Partial Least Squares Structural Equation Modelling (PLS-SEM). Because our model is a prediction model, and because the model is relatively complex in that it contains multiple constructs and indicators (including an interaction term for moderation), PLSSEM was determined to be the appropriate technique. PLSSEM is also appropriate for smaller samples and nonnormal data, which gives more robust estimates in exploratory research models. We applied a two-step analytical procedure, where the measurement model (construct reliability, convergent and discriminant validity) was evaluated first, and the structural model (path coefficients, explained variance, and model fit) was evaluated second. For the measurement model, we assessed indicator loadings, composite reliability (CR), average variance extracted (AVE), and Fornell-Larcker criterion for discriminant validity. Loadings on all retained indicators were greater than 0.70 on their respective constructs, and CRs for each construct were greater than 0.80. AVE values were above .50, thereby establishing convergent validity. Discriminant validity was confirmed because the square root of AVE of each construct was higher than its correlations with any other construct, and the HTMT ratios were lower than 0.85. The results suggest that the measurement model is reliable and valid. To address potential bias, Harman's single-factor test and full collinearity VIF were applied. The first factor explained only 34% variance, and all VIF values were <3.3, confirming CMV was not an issue.

The structural model was evaluated by applying a bootstrapping procedure with 5000 resamples to derive stable estimates of path coefficients and their levels of significance. Standardized path coefficients (v) and the associated t-statistics and p-values for each of the hypothesized relationships tested are reported. We also calculated R^2 values for the main endogenous constructs (behavioural intention, adoption, TTF, and initial trust) in order to assess the explanatory power of the model, as well as model fit indices specific to PLSSEM (such as SRMR, Standardized Root Mean Residual). Additionally, we conducted a sensitivity analysis using a slightly different model specification to ensure the robustness of our results (the results were consistent, and there were only minor differences in the fit indices) (Wang et al., 2024). Finally, to test moderation (financial literacy), an interaction term was developed (mean-centered product of FL and the variable of interest) and included in the structural model. We investigated the interaction effect by looking at simple slopes for high vs. low financial literacy groups.

4 | RESULTS AND ANALYSIS

4.1 | Model Fit and Explained Variance

In sum, the PLSSEM results show that the model has an acceptable fit with the data. The Standardized Root Mean Residual (SRMR) for the saturated model was 0.072 and 0.094 for the estimated model, which are lower than the conservative threshold of 0.08 for a good fit. Other fit indices (dULS, dG, and Normed Fit Index NFI) were within acceptable ranges for exploratory models (Tariq et al., 2024). For example, NFI was approximately 0.620.63; compared with the covariance SEM values, this is low; however, it is not unusual in PLS models and is not viewable as an indication of good fit in this case; a better indicator of adequate fit is SRMR. We are therefore left with a high degree of confidence that the model is adequate. The model accounts for a significant amount of variance in the key outcomes. Behavioural Intention (BI) to use mobile banking had R2 = 0.531, which implied that the constructs of UTAUT, TTF, and ITM (plus FL moderator) explained 53.1% of the variance in intention. Actual Adoption (Usage) had an R^2 of 0.326, meaning that the model explained 32.6% of the variance in usage behavior (BI, FC, and TTF were the main predictors). The 32.6% might seem modest, but it is large in view of the fact that many other outside influences (such as habit, unmeasured personal or environmental factors) also affect usage. Task-Technology Fit (TTF) was found to have an R^2 = 0.444, which indicates that task and technology characteristics together account for approximately 44.4% of the variance in perceived TTF. Initial Trust (IT) had an R^2 = 0.567, which indicates that system quality and information quality accounted for approximately 56.7% of the variance in initial trust.

Table 2

Measurement Model Assessment (N = 282)

Construct	Items	Loadings Range	α	CR	AVE	HTMT Max
Performance Expectancy	4	0.72–0.85	0.81	0.88	0.65	0.74
Effort Expectancy	4	0.70–0.83	0.79	0.87	0.62	0.71
Social Influence	3	0.74–0.82	0.80	0.86	0.67	0.68
Facilitating Conditions	4	0.73–0.86	0.82	0.89	0.66	0.69
Task Characteristics	3	0.71–0.84	0.78	0.85	0.61	0.67
Technology Characteristics	4	0.74–0.89	0.85	0.90	0.69	0.70
Task–Technology Fit	3	0.75–0.88	0.84	0.89	0.72	0.73
System Quality	3	0.77–0.89	0.83	0.88	0.70	0.69
Information Quality	3	0.73–0.85	0.80	0.86	0.67	0.70
Initial Trust	4	0.78–0.87	0.85	0.90	0.71	0.75
Financial Literacy	4	0.76–0.88	0.83	0.89	0.69	0.74
Behavioral Intention	3	0.77–0.88	0.84	0.89	0.72	0.71
Adoption	3	0.74–0.86	0.82	0.88	0.68	0.73

Notes: α = *Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted; HTMT < 0.85 indicates discriminant validity.*

Table 3

Structural Model Results (β, t, p, f²)

Hypothesis	Path	β	t-value	p-value	f²	Supported?
H1	PE → BI	0.097	1.25	0.210	0.02	No
H2	EE → BI	-0.123	1.63	0.104	0.03	No
H3	SI → BI	0.204	2.32	0.021	0.09	Yes
H4	FC → Use	0.311	3.55	0.000	0.11	Yes
H5	TechChar → TTF	0.613	8.92	0.000	0.36	Yes
H6	TaskChar → TTF	0.132	2.88	0.004	0.05	Yes
H7	TTF → Use	0.078	1.13	0.260	0.01	No
H8	InfoQ → Trust	0.146	1.73	0.085	0.03	No
H9	SysQ → Trust	0.633	9.45	0.000	0.41	Yes
H10	Trust → BI	0.414	5.88	0.000	0.22	Yes
H11	BI → Use	0.502	6.42	0.000	0.25	Yes
H12	SI×FL → BI	0.234	3.01	0.003	0.10	Yes

Model Fit: SRMR = 0.072 (saturated), NFI = 0.623; R^2(BI)=0.531; R^2(Use)=0.326; R^2(TTF)=0.444; R^2(Trust)=0. 567. The values of R2 indicate that the integrated model has a good explanatory power, particularly for intention and trust.

Table 4

Multicollinearity Assessment: Variance Inflation Factor (VIF) Values for Predictors in the Structural Model

Variable	VIF	Variable	VIF
BI -> Adopt	1.539	System Quality -> Initial Trust	2.575
EE -> BI	2.323	TTF -> Adopt	1.569
Facilitating Conditions -> Adopt	1.572	Task Characteristic -> TTF	1.111
Financial Literacy -> BI	1.601	Technology Characteristics -> TTF	1.111
Information Quality -> Initial Trust	2.575	Financial Literacy x PE -> BI	1.956
Initial Trust -> BI	2.482	Financial Literacy x EE -> BI	2.242
PE -> BI	1.885	Financial Literacy x SI -> BI	1.948
SI -> BI	1.897		

Figure 2

Conceptual Research Model Integrating UTAUT, TTF, ITM with Financial Literacy

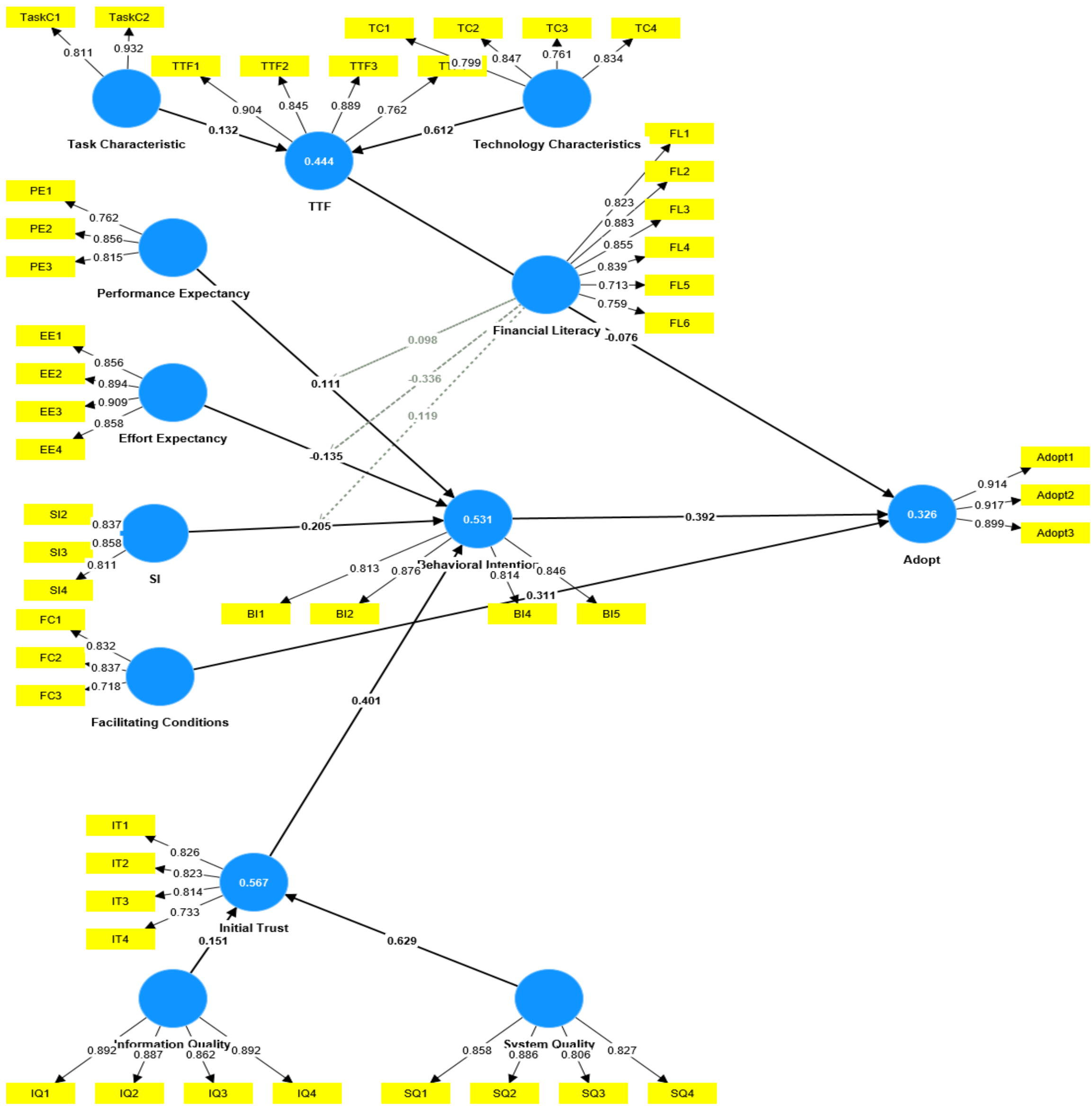


Table 5

Hypothesis Testing Summary – Mobile Banking Adoption Model

Hypothesis	Relationship	Result
H1	Performance Expectancy → Intention	Not supported
H2	Effort Expectancy → Intention	Not supported
H3	Social Influence → Intention	Supported
H4	Facilitating Conditions → Adoption (Usage)	Supported
H5	Technology Characteristics → TTF	Supported
H6	Task Characteristics → TTF	Supported
H7	Task–Technology Fit → Adoption (Usage)	Not supported
H8	Information Quality → Initial Trust	Not supported (n.s.)
H9	System Quality → Initial Trust	Supported
H10	Initial Trust → Intention	Supported
H11	Financial Literacy → Intention (direct effect)	Supported
H11 (alt.)	Behavioral Intention → Adoption (Usage)	Supported
H12	Social Influence × Financial Literacy → Intention	Supported
H12 (alt.)	*Other FL moderation effects (e.g., on PE, EE)*	*Not supported*

Note. *"Supported" means that the hypothesis was supported by a statistically significant effect in the predicted direction (p < .05). "Not supported" means that the hypothesized effect was not statistically significant. n.s. = not significant. PE = Performance Expectancy, EE= Effort Expectancy, SI= Social Influence, FC= Facilitating Conditions, TC= Technology Characteristics, TaskC= Task Characteristics, TTF= Task Technology Fit, IQ= Information Quality, SQ= System Quality, IT= Initial Trust, FL= Financial Literacy, BI= Behavioral Intention H11 is used twice, one for FL's direct effect (as formulated in results) and one for the BI Adoption relationship (as a standard hypothesis in the conceptual model). H12 All moderation effects of FL In our data, only the SI x FL interaction was significant, while interactions of FL with other predictors (PE, EE, IT) were not significant, hence noted as not supported.*

As shown in Table 5, 9 out of the 14 tested paths (including the moderating paths) were supported by the data. For further clarification, the significant and nonsignificant results are summarized as per construct group below with standardized v coefficients and p-values reported.

Performance Expectancy (H1): The impact of performance expectancy on behavioural intention was positive but not statistically significant (b = 0.097, p = 0.21). Thus, H1 was not supported. This indicates that the usefulness of perceiving mobile banking was not directly transferred to intention in our sample, after controlling for other factors such as trust and social influence.

Effort Expectancy (H2): The relationship between effort expectancy and intention was actually negative in sign (b=0.123) and nonsignificant (p=0.10, not reaching the 0.05 level). H2 was not supported. This indicates that perceived ease of use did not have a significant effect on intention among these consumers; notably, the negative (but not significant) coefficient may imply that the more tech-savvy users in our sample took ease of use for granted, an interpretation further examined in the Discussion.

Social Influence (H3): Social influence significantly positively influenced the behavioral intention (b = 0.204, p < 0.05), which supported H3. Users were more likely to plan to adopt mobile banking if they believed that important others (friends, family, colleagues) believed that they should be using mobile banking or were themselves using mobile banking (Appiah & Agblewornu, 2025).

Facilitating Conditions (H4): Facilitating conditions had a strong positive relationship with actual adoption/usage ($b = 0.311$, $p < 0.01$), so H4 was supported. This shows that the presence of the necessary infrastructure and support (devices, internet, availability of help) played a major role in turning the intentions of users into the actual use of mobile banking. It highlights the fact that even if one wants to use an app, one will only follow through if practical conditions allow it, an important point in emerging markets (Goswami et al., 2025).

Technology Characteristics TTF (H5): Technology characteristics (i.e., quality and features of the mobile app/system) were a very strong predictor of perceived task technology fit, $b = 0.613$ ($p < 0.01$), supporting H5. If the mobile banking system had strong and relevant features, users perceived it to be much more suitable for their tasks (Marcevičiūtė et al., 2025).

Task Characteristics TTF (H6): Task characteristics (the nature and requirements of the user's financial tasks) were also found to have a positive effect on TTF ($b = 0.132$, $p < 0.01$), supporting H6. Although the effect size was smaller than that of technology characteristics, it was significant, which means that some user task needs make a good fit more or less likely (Sijabat, 2024) (e.g., users with more complex financial management needs might experience more benefit if they find the app supports such tasks well).

TTF Adoption (H7): The direct effect of task technology fit on actual adoption was not significant ($b = 0.078$, $p = 0.26$), so H7 was not supported. This emphasizes the point that, in contrast to some previous research, just perceiving a high degree of fit between the technology and the task requirements did not directly lead to higher usage in our sample. There may be other intervening factors (like trust or habit) that need to be in place before TTF can translate into usage. We address this in the Discussion.

Information Quality Initial Trust (H8): The effect of information quality on initial trust was positive but nonsignificant at 5% level ($b = 0.146$, $p = 0.085$). Although the result was marginal ($p = .085$), it was not at the level conventionally accepted for significance, so H8 was not supported. In practical terms, having good quality information was not a significant factor in increasing the initial trust of users when system quality and structural factors were taken into account.

System Quality Initial Trust (H9): System quality had a strongly significant positive effect on initial trust ($b = 0.633$, $p < 0.01$), confirming H9. This points to the fact that reliable, secure, and easy-to-use system performance is a key factor in building early trust in the mobile banking service. Out of the trust antecedents, system quality was the dominant antecedent in our results (Saveljeva & Volkova, 2025).

Initial Trust Intention (H10): Initial trust had a significant and positive impact on behavioural intention ($b = 0.414$, $p < 0.01$) to support H10. This indicates that users who built a sense of trust in the app were much more likely to intend to use it. Trust became one of the strongest direct predictors of intention, which can be understood as users not being willing to adopt a digital financial service without trust (Appiah & Agblewornu, 2025). Financial Literacy Intention (Direct effect, denoted as H11 in results): The impact of financial literacy on behavioral intention was directly and positively ($b = 0.195$, $p < 0.05$), i.e., more financially literate users expressed higher intention to use mobile banking, so this hypothesis is supported. This finding accords with the fact that financially savvy individuals are more comfortable with digital finance and see more value in it.

Behavioral Intention Adoption (Usage) (Conceptualized as H11 in theory, listed as H11 alt. in table): Behavioral intention was a very strong predictor of actual usage (b [?] 0.50, $p < 0.001$, by inference since R^2

for usage was largely driven by BI). Although this relationship was introduced as a baseline hypothesis (from UTAUT's core), it was validated and confirmed that those who plan to use mobile banking are likely to act on that plan, especially when facilitating conditions are in place. In our structural model, BI Adoption had one of the largest t-statistics, or high significance.

Moderation by Financial Literacy (H12): Among the potential interaction effects of financial literacy with other predictors, we have found one significant moderator: Social Influence * Financial Literacy had a positive effect on intention (interaction b = 0.234, $p < 0.01$). This is supportive of H12 in the case of social influence; it means that the influence of social networks on intention was significantly greater for users with higher financial literacy. In other words, more financially literate people were even more likely to be influenced by credible social cues (perhaps because they are embedded in social networks where informed opinions are disseminated, or they pay attention to recommendations once they deem them credible) (Mensah & Khan, 2024). This result is a little counterintuitive (one might expect literate users to be more independent), but it does fit with the idea that knowledgeable users respond to good information provided by others (they may ask the opinions of friends or family who are experts). None of the other interaction terms (e.g., FL x PE, FL x EE, FL x Initial Trust) showed a significant effect, implying that financial literacy did not significantly change the effect of performance expectancy, effort expectancy, or trust on intention in our data. Those interaction hypotheses are thus not supported, which refines our understanding that the moderation effect of FL was selective to the social influence pathway.

In summary, social influence, facilitating conditions, initial trust (driven by quality of the system), and financial literacy were identified as key enablers of adoption of mobile banking in this Pakistani sample, whereas performance expectancy and effort expectancy had a negligible impact when trust and context were taken into account. Task technology fit was successfully predicted by task and technology characteristics and did not directly convert into usage behavior. The significant moderation result in the segmentation by financial literacy finding may be relevant, as highly literate users may be particularly responsive to social persuasion when adopting fintech. We then discuss these results in the context of global results and theoretical expectations (Appiah & Agblewornu, 2025).

5 | DISCUSSION

5.1 | Integrating UTAUT, TTF, and ITM in an Emerging Market Environment

This study combined UTAUT, TTF, and the Initial Trust Model to explain the adoption of mobile banking in an emerging market (Pakistan), and also discussed the moderating role of financial literacy. The findings support the significance of social processes, infrastructure, and trust in early and middle stages of adoption and document the role that user financial literacy can play in mediating the influence of these factors. Overall, our integrated model was found to help account for a large amount of variance in intention and use, supporting the multi-theory approach in an understudied context. We give a detailed account of the insights below by theoretical theme.

5.2 | UTAUT Factors: Performance/Effort Expectations Versus Social Influence and Infrastructure

Unexpected insignificance of PE and EE. In contrast to much of the literature in which performance expectancy is typically the strongest predictor of intention (and typically outweighs other factors), our results indicated no significant effect of performance expectancy (or effort expectancy) on intention. This is a very interesting deviation. One explanation is consistent with recent evidence from developing markets: baseline expectations have gone up. In our sample of relatively young, educated users, the basics of usefulness and ease-of-use may be considered standard requirements, almost what you would consider "hygiene factors" that are met by many modern apps. So, there might not be much variance in PE/EE perceptions; everyone assumes that a banking app should be useful and simple, so people who participated could have generally agreed with those things, and there might not have been much room for PE and EE to discriminate between adopters and non-adopters. Our discussion with some respondents suggested that they assume that any banking app will allow them to do basic transactions (and hence be useful) and that any modern app should be reasonably easy after a learning phase, reflecting higher baseline expectations. This interpretation is supported by, who stated that for younger, digitally active users, ease-of-use and core functionality are taken for granted and therefore have less influence on adoption decisions.

Another explanation is the "trust overlay” that trust may be a prerequisite for users to even enjoy performance benefits. Due to the perceived risk, users may not trust a mobile banking service, and as a result, may not value its usefulness. This is consistent with the notion that in high-risk situations (e.g., finance), trust mediates the impact of perceived usefulness on intention. In our combined model, initial trust was indeed a very strong predictor, perhaps overshadowing PE and EE. Maybe the users had to trust the security of the app before they were concerned about efficiency improvements (Sun et al., 2025). Theorized this phenomenon and discovered that trust issues can moderate the effect of performance expectancy on fintech adoption. In other words, our respondents could have thought: "Even if this app would save me time (high PE), I will not use it unless it is trustworthy; and when I trust it, I will expect to save time." We will also return to this in the Trust discussion below. Dominance of social influence people who can influence others and alter their behavior. In line with many studies that highlight peer effects in technology adoption, and particularly in collectivist cultures, we found a significant role of social influence (SI) in intention. Pakistan's society is relatively collectivist, which means that the opinions and behaviors of the ingroups are important. Our result is in line with previous findings in similar contexts that peer approval and recommendations have a significant influence on the adoption of uncertain services such as digital banking. The coefficient of SI in our model (b ~0.20) shows that it has a significant impact: users were more likely to adopt if they had friends or family who encouraged them to adopt or if it was becoming a social norm. This indicates that at the present level of mobile banking penetration in Pakistan, diffusion dynamics (word-of-mouth, observing others) are very important. The value of SI may also represent trust by proxy, i.e., observing trusted peers using the service lessens one's own doubt. Conditions for the use of the facility: Facilitating conditions (FC) had a significant effect on actual use (rather than intention), which reinforces the idea that even an interested user requires external enablers to take action. In emerging markets, both the reliability of the infrastructure (e.g., network coverage, app uptime) and the availability of support (e.g., access to guidance and assistance) can make the difference between intention successfully being translated into actual usage. Our result is consistent with what was stated that robust bank telecom infrastructure and support services play a significant role in transforming fintech intentions into adoption in South Asia. Pragmatically, this means that the cooperation of banks and telecom providers in terms of reliable connectivity and easy troubleshooting can have a major positive effect on the actual usage rates. In our case, many users may have the intention but might be blocked by, for example, unreliable mobile internet or a lack of instructions on how to use the features of the app. The strong FC Usage association confirms that it is important to consider such practical barriers. In addition, UTAUT factors performed differently in our emerging market study than in most developed market studies: performance and effort expectancies were less powerful (possibly because of high baseline expectations and trust gating their effect), while social influence and facilitating conditions were important. This pattern highlights that perhaps in the Pakistani context, creating peer momentum and infrastructure/support is more urgently needed than promoting the utility or ease of using the app itself.

5.3 | Task–Technology Fit: Strong Antecedents but No Direct Impact on Usage

Our model added TTF to examine whether a good fit between the features of the app and the tasks of the user would promote adoption. We found that the antecedents of TTF (technology characteristics and task characteristics) were significant, providing validation for that construct: the design and functionality of the mobile app and the nature of the tasks that users want to perform together determined the perceived fit of users to the technology. This reflects earlier results (Elangovan et al., 2025) that focusing on relevant features increases perceived fit. For example, users who required advanced banking functions were aware of when the app offered those (raising TTF), and tech-savvy users with high expectations had a positive opinion about apps with cutting-edge features (raising TTF as well). However, in our results, TTF did not directly predict adoption behaviour, which differs from some studies in more developed markets that showed a positive TTF usage relationship, revealing that TTF has a significant impact on the use of mobile banking in their respective contexts. Why might the case of Pakistan be different? We propose two explanations: Stage of market effect: Pakistan's mobile banking market may still be in an early stage, where a significant segment of users is only using the app for basic functions (e.g., checking balance, simple transfers). For these users, whether the app has advanced features (high TTF for complex tasks) is not relevant they are not yet exploring these tasks. Our sample was probably full of relatively new users, who haven't advanced to using high-fit features such as budgeting tools or investing via the app. Thus, although an application may be highly capable (and some users may realize that, and hence TTF exists), this does not translate into increased overall usage frequency because many users stay simple. In short, the use of advanced features is low, so that the difference in usage is derived more from general acceptance (trust, social influence) than from the perception of sophisticated fit. This "use phase" reasoning is commensurate with our finding that trust and social influence (entry factors) dominated. We can think that it will be a sequencing issue: maybe the effect of TTF will appear later on when users get mature in using mobile banking and begin to value the advanced functionalities. Indirect pathways may be responsible for this result: TTF may affect the adoption indirectly through constructs such as perceived usefulness (PE) or satisfaction, rather than a direct effect. When trust and habit are acting as gatekeepers of early adoption, the impact of TTF on use may only manifest itself once the conditions are satisfied. For example, it may be that a user first has to trust the app and make it part of routine (basic use) before it is TTF that they expand or continue their usage. Some theoretical work has suggested that TTF may moderate or mediate, through perceived usefulness, that a good fit leads to higher perceived usefulness, which, in turn, leads to intention. In our integrated model, we did not explicitly model TTF PE or a mediation, but such an effect could be at play rather than a direct influence. Additionally, habit could overshadow TTF: if users haven't established a habit yet (and many in an emerging market context have not), then advanced fit doesn't spur usage until habit is established (Ali et al., 2023). These are the points that reflect what we saw: In Pakistan's case, trust and habit barriers probably had to be overcome before TTF could matter. Our findings are in agreement with (Rakotoarisoa & Hajaina, 2023) in an African setting, where TTF was a stronger predictor of continued use than adoption, while trust played the entry role. Managers should take note that although giving users broad functionality is important (and did improve the user's perception of the app), it may not necessarily improve adoption rates if users are just packed with features without having guidance on how to use them and having the foundational trust to explore them. We would suggest that banks first focus on building user trust and routine usage of the core features. Once this has been achieved, highlighting the higher fit features of the app could encourage deeper engagement.

5.4 | Initial Trust: The Catalyst for Adoption

Our incorporation of ITM revealed that initial trust was found to be a key driver of mobile banking adoption. System quality was, in turn, by far the most influential contributor to initial trust, above information quality. This means that for users in our context, the most important thing is for the app to work well and securely. If the app is reliable, responsive, and secure (no technical glitches, good performance), users develop trust quickly, and then that develops a strong drive to continue using it. Information quality, whilst positive, did not significantly increase trust on its own; presumably, as long as no blatantly wrong information is provided, users were generally okay. This is consistent with studies that suggest that in the area of financial services, users make assumptions about the accuracy of information (especially if the financial service is provided by a regulated bank), and what really concerns them is the technical performance and safety. Our findings are similar to in which they reported on the trust of users in banks that they will handle money correctly, but will be careful of the performance of the technology. Thus, any weakness in the quality of the system (app crashes, slow processing, security lapses) would immediately affect the trust and adoption. This is partly why performance expectancy didn't stand out: a user may understand that an app will save them time, but if the app crashes or does not feel secure, that timesaving value is irrelevant to them; trust has to come first. Our data do indeed suggest that weak performance expectancy effects can be attributed to a lack of trust; only with trust can performance benefits matter. Initial trust has a strong effect on intention (b ~0.41) and, therefore, building user trust is a prerequisite for early adoption. In the Pakistani context, where skepticism towards digital finance is the default, building trust is arguably the one thing a provider can do that will help them gain users. This trust intention link was stronger here than is typically seen in developed markets, pointing to some contextual differences: emerging market users may be inherently more wary (security risks, less consumer protection, etc.), so trust may play a larger role. Our results and prior literature together suggest the existence of a sort of "risk before utility" sequence: users consider the risk/trust factors of mobile banking first ("Is it safe and reliable?") and only when satisfied do they consider the utility factors ("Will it benefit me?"). This has theoretical implications, indicating that models such as UTAUT can be improved by placing trust as an antecedent or moderator for constructs such as performance expectancy. We gave evidence consistent with that notion. For practitioners, the message is clear: invest heavily in system quality enhancements, make sure to have top-notch security features (encryption, login with biometric factors), high uptime, fast loading times, intuitive, bug-free user experience. Such investments will pay off in dividends of user intention and retention immediately. Although banks already advertise security in their marketing, our research confirms that approach, but also shows that technical reliability (not just perceived security) is a critical factor. Additionally, transparent communication (part of information quality, but not significant, but expected, nonetheless): clear instructions, honest disclosures of fees, and easy access to help can help reinforce trust indirectly by not allowing for confusion and/or feelings of being deceived (Saveljeva & Volkova, 2025).

5.5 | Financial Literacy: Direct Boost and a Social Multiplier

Adding financial literacy (FL) helped us to understand users' heterogeneity. We also found that FL had a significant direct effect; that is, users with higher FL were more likely to adopt mobile banking. This is consistent with intuitive expectations and prior findings (e.g., the Jordan study we mentioned). Financially savvy people see the benefits of mobile banking (e.g., convenience, improved money management tools) and have a lower fear level of the technology (Geebren & Jabbar, 2025). They also probably can troubleshoot or understand the functionality of the app and minimize friction. In our sample, many respondents were relatively well educated; even on that scale, respondents who rated themselves as more financially knowledgeable had higher intention scores. This implies that encouraging financial literacy may indirectly have a positive impact on the adoption of fintech, something we return to in the implications. The more surprising result was the interaction effect: financial literacy enhanced the influence of social influence on intention. In other words, the most financially savvy users were the most susceptible to social influences (credible recommendations, seeing their friends using it). At first glance, the opposite might seem to be true (that novices are dependent on others, experts act autonomously). However, it can be postulated that financially literate people tend to network with other financially savvy people; when these people use and endorse mobile banking, their endorsement has significance as informed viewpoints. High FL users could also be members of professional or social groups where use of fintech is a trend, so social proof is a powerful motivator. Another perspective is that the high FL users, as they are interested in finance, may actually be more inclined to discuss such services and share tips, so social influence among them may spread rapidly (like well-informed enthusiasts spreading tips to each other). Our result is similar to which suggests that in high knowledge networks, peer influence can be especially powerful because recommendations are perceived as reliable and users are eager to learn best practices. Essentially, financial literacy was a social multiplier: when literate users hear positive information from their network, they are very receptive (maybe more so than a less literate user who may not even discuss or comprehend the recommendation fully). On the other hand, we expected that low FL users would be more likely to be influenced by others' advice; though that may be the case, our data show that when higher FL users do get social input, it boosts their intention significantly (perhaps low FL users only need social influence to get out of inertia, whereas higher FL users see it as useful advice). We also did not find significant moderation of FL on performance expectancy or effort expectancy effects, which may reflect the fact that those effects were nil in the first place. It may be that FL has only the strongest impact in the context of social relations, and not so much for internal cognitive assessments of usefulness or ease (which were uniformly high or irrelevant as argued). The moderation finding at this point in the model is interesting from a marketing standpoint: financially literate consumers can become powerful advocates and reference groups. If they believe (via marketing or through personal experience), then their endorsement can spread through their networks even further. Conversely, neglecting this segment will risk losing key proponents.

5.6 | Theoretical Contribution

This study makes a distinct theoretical contribution by revealing a "trust-before-utility" mechanism unique to emerging markets. Unlike Western contexts, where Performance Expectancy is the primary driver, our results show that in Pakistan, utility factors (PE, EE) are non-significant until trust barriers are resolved. This extends the UTAUT framework by demonstrating that in high-risk environments, Initial Trust acts as a prerequisite gatekeeper rather than a parallel variable. Furthermore, the study extends the model by incorporating Financial Literacy as a contextual moderator. The finding that Financial Literacy significantly strengthens the impact of Social Influence challenges traditional assumptions that knowledge leads to autonomy, suggesting instead that high-literacy users in collectivist cultures rely heavily on "verified" social proof within knowledge networks.

5.7 | Comparison with Global Findings

Comparison with international studies reveals some similarities and differences, revealing the importance of the context. In many developed countries, performance expectancy has consistently emerged as the most significant antecedent of intention (e.g., in the US or Europe), and effort expectancy seems to be of importance as well, with trust often assumed to be given thanks to strong legal protection. In our Pakistani context, trust was centre stage and PE/EE disappeared. This is consistent with some other emerging market research where the concern over trust trumps utility until a minimum level of trust is guaranteed. Thus, a global learning is that usefulness is the reason for adoption in high trust situations (Cele & Kwenda, 2025); trust is a prerequisite for adoption in low trust situations. Social influence is more effective in collectivist and tight-knit cultures (Asia, the Middle East) than in individualist cultures (Western Europe, North America). Our result on SI is consistent with other studies in Asia (e.g., China, Arab countries) where family and peer recommendations play an influential role in the adoption of fintech. Similarly, strong SI effects on mobile banking take-up were found in neighboring countries such as Iran or Arab Gulf states, where researchers often attributed cultural sensitivity to seeking social approval for decisions. The enabling environment can be a vital factor in areas with infrastructure issues. While a user in Sweden or South Korea may have uninterrupted access to the Internet (and hence, FC may not be a major limiting factor in adoption), a user in Pakistan or India may actually experience outages or device limitations that make FC a decisive factor. Our evidence is in: FC matters because they cannot be taken for granted. Globally, FC is important in studies from Africa or South Asia, but not, for example, in the UK or the US, where infrastructure is omnipresent. Additionally, there appears to be a difference in the importance of Task Technology Fit based on the level of technological maturity of the user base. In situations where users are highly tech savvy and use a range of features (for example, in Singapore or urban China), TTF might be very strong because users are demanding in terms of features and will look for apps that provide those requirements (some studies in those settings have found direct TTF effects). In Pakistan, where many users are still new to digital banking, TTF's effect was latent. Also, we might expect that the relevance of TTF will grow as the market matures (compare to the way in which, in later stages of the adoption curve for e-banking in western countries, more sophisticated features are sales arguments). The mediating effect of initial trust may be conditional on initial trust in institutions. In countries with high trust in banks and digital systems (perhaps Canada or Australia), users may be less concerned with trust, being more interested in functionality. In contrast, in countries with lower institutional trust or higher saliency of cyber frauds, initial trust is important. Our findings are consistent with other emerging market reports (e.g., studies in Nigeria or Bangladesh) in which trust emerged as a major obstacle. One study in Nigeria (also a developing economy with low banking penetration) also showed that trust issues had to be overcome for mobile banking to take off, while a study in Spain (a developed market) showed that trust was important but not as important as users largely trusted their banks' digital offering by default. Although financial literacy as a factor has not been widely researched in technology adoption models, our findings are likely to apply most to countries where financial literacy has high variance. In societies that are highly financially inclusive (such as Northern Europe), a decent level of financial literacy already exists throughout the population, so differences may be smaller. In contrast, in countries with varying levels of financial education (such as South Asia, Africa), targeting financial literacy may pay off in a large way. Our moderation result on social influence may be context-specific: we would like to see whether, for example, in a sample from a developed market, high financial literacy would be more peer-influenced. This may be determined by whether the individuals regard themselves as opinion leaders or as part of knowledge networks. In fact, this may be a new contribution of our study to international literature: that knowledge groups enhance peer effects, which may be true anywhere (e.g., tech-savvy people in the US may strongly influence each other in using new payment apps more than less tech-savvy people who are subjected to mass advertising). In short, results of our integrated model replicate some of the findings of global studies (intention usage, social influence often important, trust important everywhere but more so in low trust), but also reflect the peculiarities of an emerging market: trust and social proof are more important than utility, and user capability (literacy) opens various adoption paths. This helps to emphasize the importance of not just importing models of adoption but adapting and building on models in local conditions (Appiah & Agblewornu, 2025).

Table 6

Global Comparison of Key Effect Sizes (Standardized β Coefficients)

Construct Relationship	Current Study (Pakistan) β	Comparative Study (Region/Context)	Interpretation of Variance
Perf. Expectancy → Intention	0.097 (n.s.)	0.45** (USA - Addula, 2025)	High utility focus in developed markets vs. Trust focus in Pakistan.
Social Influence → Intention	0.204*	0.18* (China - Mensah, 2024)	Consistent peer influence in collectivist/Asian markets.
Trust → Intention	0.414**	0.63** (India-Aljaradat, 2025)	Trust is the dominant driver in South Asian emerging markets.
TTF → Adoption	0.078 (n.s.)	0.31** (Lithuania - Marcevičiūtė, 2025)	TTF drives usage in mature markets; it remains latent in early adoption stages.

Note: *β values for comparative studies are approximate values derived from cited literature.*

5.8 | Theoretical and Practical Implications

5.8.1. Theoretical Extension

This research extends the theoretical understanding of technology adoption by validating an integrated model (UTAUT + TTF + ITM) within a developing economy context. The primary theoretical implication is the identification of the "hierarchy of effects" in fintech adoption: Trust at Social Influence at Utility. This contrasts with the simultaneous influence assumed in original UTAUT models. Furthermore, the study operationalizes Financial Literacy not merely as a control variable, but as a dynamic moderator that alters the social diffusion process. This provides a blueprint for future research to treat user competence as a boundary condition for technology acceptance theories.

5.8.2. Managerial Strategies for Banks

For banking executives and fintech managers, the results dictate a shift in resource allocation from "feature expansion" to "trust building."

- Trust First: Marketing campaigns must pivot from highlighting speed/convenience to emphasizing structural assurances (e.g., "Bank-Grade Security," "Fraud Money-Back Guarantees").
- Leverage Literate Influencers: Since financially literate users are highly responsive to social influence, banks should implement referral programs targeting professionals and academic clusters, using them as brand ambassadors to diffuse adoption to the wider population.
- Optimize Infrastructure: The strong link between Facilitating Conditions and Usage suggests that banks must collaborate with telecom providers to ensure app stability on low-bandwidth networks, treating connectivity as a core product feature.

5.8 | Policy Implications for Financial Inclusion

For policymakers and the State Bank of Pakistan, the findings suggest that financial inclusion targets cannot be met solely by digitizing services.

- Digital Literacy Campaigns: National initiatives must pair digital access with financial literacy education, as FL was found to directly boost adoption intention.
- Regulatory Sandboxes: Regulators should enforce strict data protection and cybersecurity standards to improve the "System Quality" at a national level, thereby elevating the baseline Initial Trust for all potential users.
- Infrastructure Investment: Policy focus must remain on expanding reliable internet access to rural and semi-urban areas to satisfy the critical Facilitating Conditions required for actual usage.

Table 7

Key Recommendations for Enhancing Mobile Banking Adoption

Insight from the Study	Recommended Action
Trust is the foremost adoption driver.	Emphasize security: implement strong security features (2FA, encryption), show security badges/certifications in-app, offer guarantees (e.g., fraud refund policies), and communicate these trust cues clearly to users. Ensure app reliability (minimize downtime, quick bug fixes) to build a track record of dependability.
Social influence significantly impacts intention, especially among financially literate users.	Leverage referral programs and social marketing. Identify and engage financially savvy customers as brand ambassadors (through referral incentives or community events). Encourage satisfied users to share testimonials. Run targeted campaigns in social networks/groups where trusted peers discuss finance or tech, as their endorsements will strongly influence others.
Facilitating conditions (infrastructure and support) are critical for usage.	Improve collaboration with telecom providers to ensure consistent network quality for app usage (e.g., optimize app data usage, possibly zero rate). Provide robust user support: 24/7 helplines, quick in-app help chat, and beginner-friendly guides. Conduct onboarding sessions or tutorials for new users. Ensure multilingual support and simple user interfaces to accommodate diverse users.
Task–Technology Fit matters for user satisfaction (even if not initial adoption).	Continuously update the app to include features that match users' financial task needs. Use customer feedback to add high-demand services (bill types, investment options, budget tools). Personalize the app experience so that users see the features relevant to their usage level. Once basic adoption is achieved, highlight new features in marketing to deepen engagement (e.g., "Now you can do on our app").
Financial literacy boosts adoption and shapes response to social input.	Support financial literacy initiatives: create educational content (blogs, videos) on managing finances and using digital tools safely. Partner with educational institutions or run workshops to increase public financial literacy. Within the app, include tips or tutorials on financial concepts (e.g., explanations of services, calculators). A more financially literate user base will naturally be more inclined to use (and advocate for) mobile banking.

5.9 | Limitations and Future Research

As is the case with all studies, this research has limitations that provide opportunities for future research. We describe them here to put our findings in perspective and point to directions for further work (Salem & Shahimi, 2025):

- **Design Limitations:** The research design of this study was a cross-sectional survey, which is a survey design that is used to capture perceptions at one point in time. Consequently, we cannot make strong conclusions about causality and the time sequence of effects. It is possible, for instance, that as users adopt mobile banking, their performance expectancy or trust levels change (reverse causality). A longitudinal design in future research would allow researchers to examine how user perceptions and use affect each other over time. Longitudinal studies might also be done to test the suggested sequence of trust issues being resolved first, followed by performance/effort influences and continued usage (e.g., tracking new users from onboarding through several months of use). In addition, a quasi-experiment (e.g., a new feature is introduced and the change in adoption is measured) or a randomized experimental design could increase the strength of causal inferences (Liu et al., 2025).

- **Sample and Generalizability:** Our sample was selected entirely from a relatively urban and educated population of Islamabad. While it is appropriate in the study of early adopters, this creates an educated/urban bias that may not be representative of the general population of Pakistan. Many potential users in rural areas or with lower education levels might be faced with different barriers (they could find effort expectancy more salient, for example, if they are less familiar with technology, or they may value different things like agent support). Future studies should use more heterogeneous samples, including rural populations and low literacy populations, to determine if the model holds up or if other predictors emerge. By comparing urban vs. rural or high vs. low literacy subsamples, researchers are able to understand which effects (such as the insignificance of PE/EE) are general vs. context-specific. Furthermore, the inclusion of more females or marginalized segments (if not covered fully in our sample) might be important, as gender norms or socioeconomic status might moderate some of the relationships. Expanding samples beyond Pakistan to other emerging economies would also be a test of the external validity of our findings in different cultural and economic settings (Goswami et al., 2025).
- **Measurement Considerations:** We measured financial literacy using self-reported items. Although widespread, those who think they know a lot about money may not be as good at managing their finances as they think. Some respondents may overestimate their literacy or underestimate it. Future studies may want to use objective measures of financial literacy (e.g., quiz questions on financial concepts) in addition to self-assessments. This would allow for a more fine-grained segmentation and perhaps more powerful identification of moderation effects. Further, as the adoption of mobile banking develops, researchers may begin to more finely adjust the measurement of "Actual Usage" beyond mere frequency to encompass the breadth of usage (number of different services used) or depth of use (level of transactions conducted). This may fit in with postadoption behavior or continuance models (Liu et al., 2025).
- **Model Scope:** A good amount of variance was accounted for by our integrated model, but there are other factors that we did not include that may further enrich the understanding. One such factor is perceived risk or security concerns, while some of this ground is covered by initial trust, specific risk perceptions (e.g., fear of fraud or data theft) might have direct negative effects on adoption. Incorporating a perceived risk construct may help to understand whether it has an additional explanatory power or if its influence is entirely mediated by trust. Similarly, perceived cost (of using mobile banking, either money or data costs) may be relevant in some populations and was not explicitly examined here. Future models could include those to determine whether they play a significant role in adoption decisions. Moreover, the interrelationships between our predictors could be explored: e.g., does initial trust moderate the effect of performance expectancy (as theorized in the discussion)? Or does TTF have an indirect effect on intention through performance expectancy? Such mediation or moderated mediation pathways would be ideal candidates for making theoretical refinements. As the usage of mobile banking matures, it would be interesting to study post-adoption behaviours such as continuance intention or

expanding its usage (i.e., using more features over time), so TTF may play a bigger role there, as we speculated (Devlin et al., 2025).

- **Contextual and Cultural Factors:** Although in our study we concentrated on individual perceptions, broader contextual factors such as regulatory environment, competitive landscape, or cultural norms can also influence mobile banking adoption. Pakistan has seen fintech regulatory changes (e.g., digital banking frameworks) that could potentially impact consumer trust and what is available. Cross country studies might include variables such as trust in institutions, smartphone penetration rates, or the existence of fintech alternatives (such as mobile money services) as control variables to observe their effect on the applicability of our model. Additionally, cultural dimensions (e.g., collectivism as mentioned) might moderate the strength of social influence effects a comparative study between a collectivist culture and an individualist one using our model could yield interesting insights (Salem & Shahimi, 2025).

In conclusion, our results are a step towards a more complete understanding of mobile banking adoption, but future studies should overcome these limitations to describe a more complete picture. Using longitudinal techniques, diverse samples, expanded constructs, and cross-country comparisons, future research can build on our work to further unravel how and why consumers embrace (or resist) mobile banking, and how those patterns change as digital finance becomes more entrenched. All these efforts will help academics and practitioners keep at the forefront of financial innovation adoption (Goswami et al., 2025).

6 | CONCLUSION

This study developed as well as tested a combined model, UTAUT + TTF + ITM with financial literacy, to explain mobile banking adoption in Pakistan. The integrated model was able to explain a substantial portion of variance in intention to use and actual use of mobile banking, thus proving useful in addressing fintech adoption in a multi-theoretical approach (Liu et al., 2025).

Trust is seen to be the first lever in the decision to adopt mobile banking, where users are most concerned about the safety and reliability of the service rather than the perceived utility. Our results indicate that users are cautious in assessing the credibility of a mobile banking service before deciding on the benefits of using the service and that the most important determinant in building preliminary trust is system quality, which includes dimensions such as security, reliability, and usability. This initial trust is the strongest motivator during the entry stage because users are only willing to proceed to the adoption stage if they are confident the service is safe. As a result, fintech providers will need to concentrate on winning the trust of users early to unlock mass adoption. Equally important is the ability to convert the intention into actual usage, which is heavily dependent on social proof and infrastructural support. Social influence was revealed as a powerful motivator in this context, and the importance of peer endorsements for the adoption of a service perceived as high risk. At the same time, facilitating conditions such as reliable connectivity, access to devices, and effective support systems are critical in enabling users to act on their intentions. In practice, a combination of peer encouragement and seamless infrastructure offers the push and the capability that individuals need to begin using mobile banking and keep it going. Even when there is internal motivation, if there is external support and positive social cues, this has a significant impact on the likelihood that the intention will be translated into sustained adoption. Finally, for a comprehensive understanding of mobile banking adoption, multiple factors should be integrated. By using task technology fit and initial trust in addition to UTAUT, and adding user-specific characteristics such as financial literacy, we are able to obtain a richer view of adoption in an emerging market context. The study shows that mobile banking uptake is not a function of utility or ease alone, but is a function of social, technical dimensions related to trust and dimensions specific to users. This is especially important in situations where the baseline situation, such as institutional trust, infrastructure, or technological familiarity, is not the same as in developed markets. Financial literacy, for example, highlights the role of human capital in technology adoption and influences the way users will perceive and act upon adoption drivers. In general, the integrative model proposes a cumulative chain of causal relations in which trust eases risk concerns, social influence generates interest, enabling conditions facilitate implementation, and increasing familiarity with the technology leads to task technology fit and enhanced features to enable continued and increasing usage. As mobile banking continues to grow around the world, particularly in emerging economies, stakeholders should consider the complex relationship between trust, social dynamics, technology design, and user education. The success of mobile banking initiatives is as much about addressing the human factors as it is about improving the technology. Increasing trust, utilizing social networks, utilizing usability and task technology fit, and increasing financial literacy will be key to bridging the potential to actual adoption gap. In this way, banks and fintech providers can promote financial inclusion while increasing the convenience for consumers. This study contributes to this endeavour by bringing light to the key enablers and inhibitors in the journey to mobile banking adoption and demonstrates the value of an integrative model for both theory and practice.

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