

Digital Financial Services Adoption among Employees: Integrating Trust, Financial Literacy and Technology Self-Efficacy



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Abstract

Digital financial services have become central to financial transactions, yet adoption depends on more than access to technology. This study examines the effects of trust, financial literacy, and technology self-efficacy on digital financial services adoption among employees. Using data from 200 respondents, the model was assessed through partial least squares structural equation modelling in ADANCO 2.4.1 with 5,000 bootstrap samples. The measurement model demonstrated reliability, convergent validity, discriminant validity, and model fit. Structural results showed that trust and technology self-efficacy positively and significantly influenced digital financial services adoption, whereas financial literacy had no significant direct effect. The model explained approximately half of the variance in adoption. The findings highlight the importance of strengthening trust and digital confidence alongside financial education. The study differentiates assurance, financial knowledge, and technology confidence as adoption drivers and offers practical guidance for financial institutions and employers promoting responsible digital financial service use.

Keywords: Digital Financial Services Adoption; Trust; Financial Literacy; Technology Self-Efficacy; PLS-SEM

1. Introduction

Digital financial services (DFS) have moved from being an alternative channel to becoming a central part of everyday financial activity. Payments, transfers, account management, savings, credit, insurance and investment services are increasingly accessed through mobile applications, internet banking interfaces and platform-based financial technologies. The Global Findex 2025 shows that financial inclusion is now deeply intertwined with digital connectivity and digital safety, with account ownership and mobile-phone access reaching historically high levels worldwide (World Bank, 2025). Yet access alone does not guarantee meaningful adoption. Users must be willing to rely on a digital provider, understand the financial implications of their choices and feel capable of completing technology-mediated transactions correctly and safely. Consequently, the behavioural side of DFS adoption remains an important research problem even in settings where digital infrastructure is widely available.

Employees constitute a particularly relevant user group because they routinely encounter formal financial products through salary accounts, digital payments, taxation, insurance, savings and

workplace-linked financial arrangements. However, employees are not homogeneous in their willingness or ability to use DFS. Some users may possess adequate financial knowledge but hesitate because they distrust digital platforms; others may trust a provider but avoid advanced functions because they lack confidence in their ability to operate the technology. These differences imply that DFS adoption cannot be explained adequately by access or general technology acceptance alone.

Technology-adoption research has traditionally emphasized perceptions of usefulness, ease of use, social influence and facilitating conditions (Davis, 1989; Venkatesh et al., 2003). In digital financial contexts, however, transactions involve money, personal data and perceived vulnerability, which gives trust a particularly important role. Prior work on electronic commerce, mobile payments and mobile banking shows that trust helps users cope with uncertainty and perceived risk and can substantially influence behavioural intentions (McKnight et al., 2002; Gefen et al., 2003; Chandra et al., 2010; Singh & Srivastava, 2018; Yadav & Kalluru, 2024). Financial literacy adds a capability dimension because users must interpret financial information and understand the consequences of financial

decisions (Lusardi & Mitchell, 2014). Technology self-efficacy adds a psychological capability dimension by capturing users' confidence in performing technology-related tasks (Bandura, 1997; Compeau & Higgins, 1995). Recent digital-finance research further shows that financial and digital capabilities remain central to safe and effective DFS engagement (Kass-Hanna et al., 2022; Ravikumar et al., 2022; Pak et al., 2026).

Despite these advances, the literature remains fragmented. Trust is often studied within risk or technology-acceptance models, financial literacy is frequently examined in financial-inclusion research, and self-efficacy is commonly positioned as a technology-readiness or social-cognitive factor. Comparatively less attention has been given to their simultaneous direct effects in a parsimonious employee-focused model. This matters theoretically because the three constructs represent distinct mechanisms: trust addresses perceived relational and institutional assurance, financial literacy reflects financial knowledge and decision capability, and technology self-efficacy reflects confidence in executing digital tasks. Examining them together clarifies whether each construct contributes unique explanatory power to DFS adoption rather than appearing important only when analysed separately.

Accordingly, this study examines how trust, financial literacy and technology self-efficacy influence digital financial services adoption among employees. The research asks: to what extent do these three factors independently explain employees' adoption of DFS? The study draws on technology-acceptance logic, social-cognitive reasoning and the human-capital view of financial literacy to develop three direct hypotheses. It contributes in three ways. First, it integrates assurance, financial capability and technology confidence within one explanatory model. Second, it evaluates their relative importance rather than treating all user capabilities as interchangeable. Third, it offers practical guidance to financial-service providers and organizations by identifying whether adoption is more likely to be strengthened through trust-building, financial education, technology-confidence interventions, or a combination of these approaches.

This distinction is also important for responsible digital inclusion. Increased adoption without adequate confidence, assurance and understanding can expose users to errors, fraud concerns or inappropriate financial choices. A useful adoption model should therefore identify not only whether users have access to DFS, but also which personal and relational conditions make them willing to use those services.

2. Literature Review and Hypothesis Development

Technology acceptance provides the broad theoretical starting point for explaining why

individuals choose to use digital systems. The Technology Acceptance Model (TAM) established perceived usefulness and perceived ease of use as core antecedents of technology acceptance (Davis, 1989), while the Unified Theory of Acceptance and Use of Technology (UTAUT) consolidated multiple acceptance traditions around performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). DFS, however, differ from many ordinary information systems because use requires individuals to transfer money, disclose financial information and accept dependence on digital infrastructures and service providers. Therefore, purely instrumental beliefs about usefulness or convenience may be insufficient. This study extends the acceptance perspective by focusing on three user-side conditions that are particularly salient in digital finance: trust, financial literacy and technology self-efficacy.

Trust refers to a willingness to rely on another party, system or institution under conditions of uncertainty and vulnerability. In digital transactions, the user typically cannot directly observe the mechanisms by which personal information, authentication credentials or funds are processed. Trust therefore reduces psychological uncertainty by supporting beliefs that the service provider and the technological system will act competently, reliably and with appropriate safeguards. McKnight et al. (2002) showed that online trust is multidimensional and can include institution-based trust, trusting beliefs and trusting intentions. Gefen et al. (2003) further demonstrated that trust complements conventional technology-acceptance variables in explaining online behaviour. The relevance of trust becomes even stronger in finance because potential losses are not merely informational or functional but monetary.

In mobile-banking and mobile-payment research, trust has repeatedly been linked with adoption intention. Chandra et al. (2010) demonstrated the central role of consumer trust in mobile-payment adoption, while Zhou (2011) showed that initial trust is critical in mobile banking. Singh and Srivastava (2018) integrated trust and security with computer self-efficacy and other adoption factors in the Indian banking context. More recent evidence from India also indicates that trust relationships between users and digital financial intermediaries can shape participation in digital modes of payment (Yadav & Kalluru, 2024). The theoretical mechanism is straightforward: where users believe that a DFS platform is dependable, secure and capable of protecting their interests, the perceived uncertainty of transacting digitally declines. Trust should therefore increase the willingness to initiate and continue digital financial transactions.

H1: Trust has a positive effect on digital financial services adoption.

Financial literacy refers to the knowledge and

understanding that enable individuals to interpret financial information and make informed financial decisions. Lusardi and Mitchell (2014) conceptualize financial knowledge as a form of human capital because it can improve the quality of financial choices and the ability to navigate financial products. In a digital environment, this capability may become even more important. DFS interfaces often provide users with immediate access to transfers, credit, investment products and other decisions whose convenience can mask underlying financial complexity. Users who understand concepts such as cost, risk, interest, repayment and diversification are better positioned to evaluate these services rather than avoiding them because of uncertainty.

Empirical research generally supports a positive connection between financial literacy and engagement with digital finance, although the magnitude of the relationship varies by product and population. Kass-Hanna et al. (2022) show that financial and digital literacy jointly contribute to financial resilience, while Ravikumar et al. (2022) validate digital financial literacy as a multidimensional capability among Indian adults using DFS. Yang et al. (2023) found that financial literacy increased the use of digital finance and that the relationship was stronger for more complex services such as online borrowing and financial products than for routine mobile payments. Recent evidence from South Korea similarly shows that digital financial literacy is associated with adoption across banking, credit, investment, insurance and payment services (Pak et al., 2026). This distinction is important because it suggests that financial literacy may not exert the same incremental effect across all forms of DFS. If a service is simple, frequently used or highly standardized, knowledge may matter less after other factors such as trust and self-efficacy are considered.

Financial literacy can also reduce dependence on other people when making financial decisions. A user who understands transaction charges, privacy warnings, repayment terms or product conditions can exercise greater autonomy when dealing with digital platforms. This autonomy should lower cognitive barriers to adoption and increase perceived control. Accordingly, the study proposes a positive direct relationship between financial literacy and DFS adoption, while recognizing that the simultaneous inclusion of trust and technology self-efficacy provides a stronger test of whether financial literacy has unique explanatory power.

H2: Financial literacy has a positive effect on digital financial services adoption.

Technology self-efficacy refers to an individual's belief in their capability to perform tasks using digital technologies. Its roots lie in social-cognitive reasoning, where self-efficacy influences effort, persistence and behavioural engagement. Compeau

and Higgins (1995) established computer self-efficacy as an important determinant of individuals' reactions to and use of information technology. Applied to DFS, technology self-efficacy reflects confidence in completing actions such as navigating a financial application, entering information, authenticating a transaction, resolving minor problems and learning unfamiliar digital functions.

Self-efficacy is conceptually different from objective skill. Social cognitive theory argues that efficacy beliefs shape effort, persistence and behavioural engagement (Bandura, 1997). Two users with similar technical knowledge may therefore behave differently if one is confident and the other is anxious about making mistakes. This distinction is especially consequential in finance, where an incorrect action may be perceived as costly or irreversible. High technology self-efficacy should reduce avoidance, increase willingness to explore service features and improve persistence when users encounter unfamiliar interfaces or procedures. Evidence from mobile-banking and fintech research supports this logic. Singh and Srivastava (2018) included computer self-efficacy among important antecedents in mobile-banking adoption, while Lee (2021) demonstrated the relevance of digital technology self-efficacy to fintech usage intention. Cross-country evidence also emphasizes the role of computer self-efficacy in mobile-banking intention (Malaquias et al., 2021).

The employee context makes this relationship particularly relevant because exposure to digital technologies at work does not necessarily translate into confidence in digital financial tasks. Financial transactions may be perceived as more sensitive than routine workplace technologies. Employees who believe they can competently use digital tools should be more willing to manage financial activities independently and to adopt a wider range of DFS. Thus:

H3: Technology self-efficacy has a positive effect on digital financial services adoption.

The conceptual model therefore positions trust, financial literacy and technology self-efficacy as three exogenous latent variables with direct paths to digital financial services adoption. No mediation or moderation is specified in the conceptual model. This parsimonious structure allows the study to compare the unique contribution of an assurance-based factor, a financial-knowledge factor and a technology-confidence factor while controlling for their shared variance.

Taken together, these hypotheses deliberately avoid assuming that one broad notion of "digital readiness" is sufficient. The model instead tests whether trust, financial understanding and technology confidence remain distinguishable when estimated together, thereby providing a direct comparison of their relative explanatory roles in the same adoption decision (figure 1)

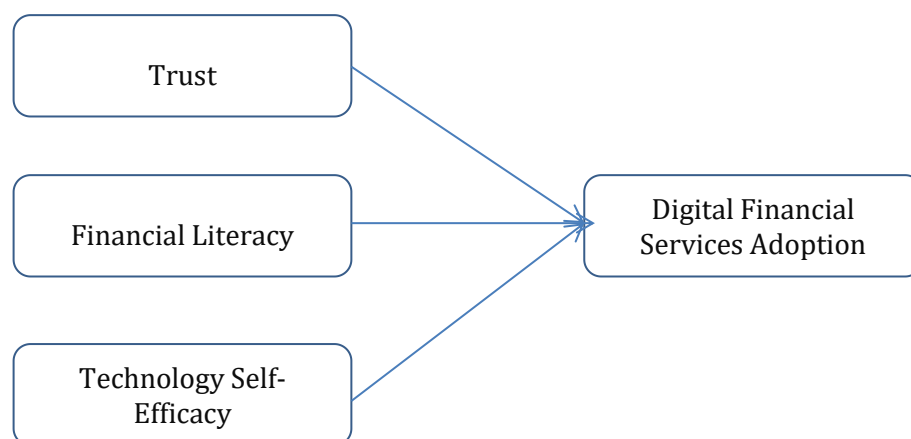


Figure 1: Conceptual Model

3. Methodology

The empirical study used structural equation modelling to estimate the direct effects of trust, financial literacy and technology self-efficacy on digital financial services adoption among employees. The final analytical sample comprised 200 observations. The dataset contained four latent constructs represented by 25 indicators: trust (TR) with five indicators, financial literacy (FL) with six indicators, technology self-efficacy (TSE) with six indicators and digital financial services adoption (DFSA) with eight indicators. The observed item values ranged from 1 to 5, consistent with the response scale used in the analysed dataset. The sample size of 200 provides adequate statistical power for the specified parsimonious model. As a conservative regression-equivalent benchmark, a model with three predictors requires approximately 77 observations to detect a medium effect ($f^2 = .15$) at $\alpha = .05$ with .80 power (Cohen, 1988). The available sample is therefore well above this minimum benchmark. The structural model contains one endogenous construct and three direct paths, making 200 observations appropriate for stable estimation and bootstrap-based inference. All four constructs were specified as reflective latent variables in ADANCO using Mode A consistent estimation. Trust was operationalized by five items (TR1-TR5), financial literacy by six items (FL1-FL6), technology self-efficacy by six items (TSE1-TSE6), and digital financial services adoption by eight items (DFSA1-DFSA8). The conceptual positioning of the constructs follows established literature on digital trust, financial capability and self-efficacy (McKnight et al., 2002; Lusardi & Mitchell, 2014; Compeau & Higgins, 1995). Recent digital-financial-literacy research further supports treating financial knowledge and digital capability as distinct but complementary dimensions of effective DFS use (Kass-Hanna et al., 2022; Ravikumar et al., 2022; Pak et al., 2026).

Data analysis was conducted in ADANCO version

2.4.1. The iterative algorithm converged after five iterations. The stop criterion was 1.0×10^{-6} , the maximum number of iterations was 200, the inner weighting scheme was Factor, model-fit assessment was enabled, and missing values were handled through casewise deletion. Consistent partial least squares (PLSc) is suitable when reflective latent variables are conceptualized as common factors because it corrects conventional PLS estimates for attenuation and yields consistent factor correlations and structural estimates (Dijkstra & Henseler, 2015). It is also well suited to integrated measurement- and structural-model assessment in technology-adoption research (Henseler et al., 2016). The analysis followed two stages. First, the measurement model was evaluated through indicator loadings, Dijkstra-Henseler's rho (ρ_A), Jöreskog's composite reliability (ρ_c), Cronbach's alpha, average variance extracted (AVE), cross-loadings, the heterotrait-monotrait ratio (HTMT) and variance inflation factors. Reliability coefficients around or above .70 and AVE values above .50 were used as evidence of internal consistency and convergent validity. HTMT was used as the principal discriminant-validity criterion because it provides a more sensitive assessment of construct distinctiveness than traditional approaches (Henseler et al., 2015).

Second, the structural model was assessed using the coefficient of determination (R^2), standardized path coefficients, Cohen's f^2 effect sizes and bootstrap inference. Statistical significance was evaluated using 5,000 bootstrap samples, two-sided p-values and percentile confidence intervals. Overall model fit was examined using SRMR, dULS and dG together with their bootstrap reference quantiles. No mediation or moderation paths were specified in the conceptual model; therefore, the hypothesis tests concern the three direct effects on DFSA. To support robust interpretation, the analysis also reviewed indicator distributions, cross-loadings, inter-construct correlations and collinearity diagnostics. The combination of reliability, validity, model-fit,

explanatory-power, effect-size and bootstrap evidence provides a comprehensive basis for evaluating the proposed model rather than relying on a single statistical criterion.

4. Results

The final ADANCO analysis used 200 observations. Preliminary inspection of the 25 indicators showed that each variable used the full 1-5 response range. Indicator means ranged from 2.81 to 3.17, skewness ranged from -0.268 to 0.126 and kurtosis ranged from -0.992 to -0.545. These distributions do not indicate severe univariate non-normality. The iterative algorithm converged after five iterations, and 5,000 bootstrap samples were evaluated successfully. Missing values were handled through casewise deletion, consistent with the ADANCO

analysis settings.

The measurement model demonstrated strong construct-level reliability. Dijkstra-Henseler's ρ_A ranged from .886 for trust to .923 for DFSA, Jöreskog's ρ_c ranged from .882 to .920, and Cronbach's alpha ranged from .883 to .921. Convergent validity was also acceptable because AVE exceeded .50 for all constructs: trust = .601, financial literacy = .596, technology self-efficacy = .610 and DFSA = .592. Most standardized loadings were around or above .70. A small number were lower, including FL2 (.511), FL5 (.686), TSE5 (.678), DFSA7 (.645) and TR4 (.695). Nevertheless, all loadings were statistically significant in bootstrap inference, and the corresponding construct-level AVE and reliability values remained acceptable, supporting retention of the measurement structure

Table 1. Measurement model assessment

Construct	Indicators	Loading range	ρ_A	ρ_c	Alpha	AVE
Trust (TR)	5	.695-.819	.886	.882	.883	.601
Financial Literacy (FL)	6	.511-.872	.911	.896	.901	.596
Technology Self-Efficacy (TSE)	6	.678-.841	.906	.903	.904	.610
Digital Financial Services Adoption (DFSA)	8	.645-.836	.923	.920	.921	.592

Note. All construct reliability coefficients exceed .88; all AVE values exceed .50. HTMT values range from .248 to .639.

Discriminant validity was satisfactory. HTMT values ranged from .248 to .639, with the largest value observed between financial literacy and technology self-efficacy (.639). All values were below .85. The 95% bootstrap upper quantiles for HTMT also remained below .85, providing additional support for discriminant validity. The Fornell-Larcker results were consistent with this conclusion. Indicator-level VIF values ranged approximately from 1.78 to 2.95, suggesting no serious multicollinearity among the indicators.

Overall model fit was acceptable. For both the saturated and estimated models, SRMR was .0522,

below its 95% bootstrap quantile of .0644. The discrepancy measures dULS (.8866) and dG (.4253) were also below their respective 95% bootstrap quantiles, indicating that the observed discrepancies were not excessive relative to the bootstrap reference distribution.

The structural model explained 50.79% of the variance in digital financial services adoption ($R^2 = .5079$; adjusted $R^2 = .5004$), indicating moderate explanatory power. Trust had the strongest positive effect on DFSA ($\beta = .4368$, $SE = .0608$, $t = 7.1794$, $p < .001$, 95% CI [.3158, .5561]). Its effect size was substantial relative to the other predictors ($f^2 = .3083$). Thus, H1 was supported

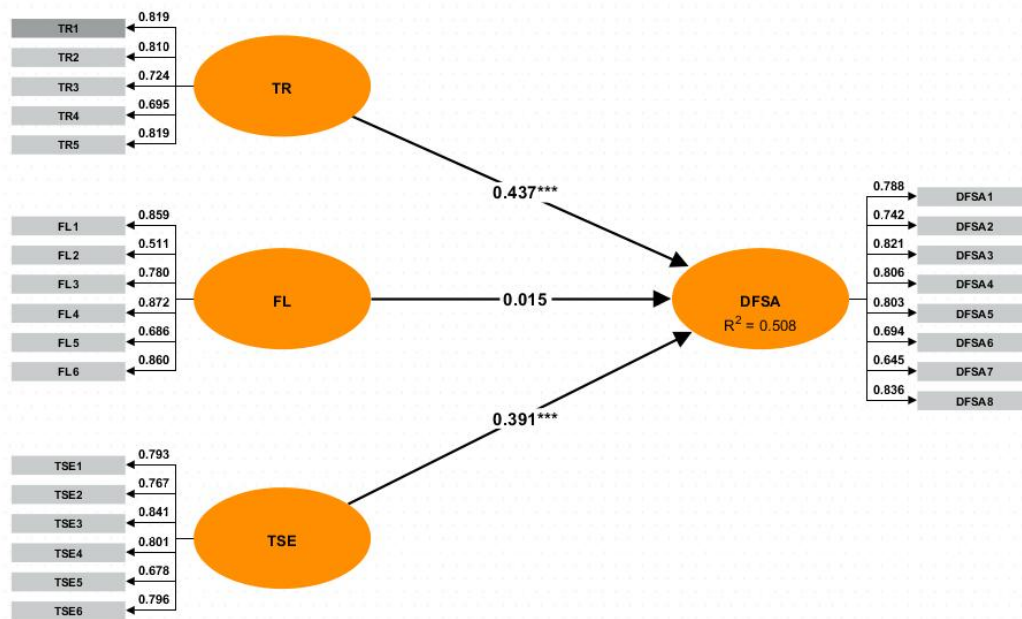


Figure 2. Estimated structural model from ADANCO

Note. *** $p < .001$. Values shown on the indicators are standardized loadings.

Financial literacy showed a very small and statistically non-significant direct effect on DFSA ($\beta = .0145$, $SE = .0805$, $t = .1802$, $p = .857$, 95% CI $[-.1322, .1893]$, $f^2 = .0003$). The confidence interval included zero and the effect size was negligible. Therefore, H2 was not supported.

Technology self-efficacy had a positive and statistically significant effect on DFSA ($\beta = .3906$, $SE = .0865$, $t = 4.5175$, $p < .001$, 95% CI $[.2107, .5523]$). Its effect size was moderate ($f^2 = .1574$), supporting H3. No indirect effects were specified or estimated. Taken together, the results show that trust and technology self-efficacy make meaningful unique contributions to DFS adoption, whereas financial literacy does not add a significant direct effect once the other two predictors are included.

Table 2. Structural model and hypothesis testing

Hyp.	Path	β	SE	t	p (2-sided)	95% CI	Decision
H1	TR → DFSA	.4368	.0608	7.1794	< .001	[.3158, .5561]	Supported
H2	FL → DFSA	.0145	.0805	.1802	.857	[-.1322, .1893]	Not supported
H3	TSE → DFSA	.3906	.0865	4.5175	< .001	[.2107, .5523]	Supported

Structural explanatory power: $R^2 = .5079$; adjusted $R^2 = .5004$. Effect sizes: TR $f^2 = .3083$; FL $f^2 = .0003$; TSE $f^2 = .1574$.

Additional diagnostics reinforce the measurement-model conclusion. Cross-loadings showed that each indicator loaded highest on its intended construct. Fornell-Larcker squared correlations were below the corresponding AVE values on the diagonal. The highest inter-construct correlation was between financial literacy and technology self-efficacy ($r = .6346$), followed by trust and DFSA ($r = .6167$) and technology self-efficacy and DFSA ($r = .5968$). These associations are meaningful but remain below levels that would suggest construct redundancy.

5. Discussion

The study examined whether trust, financial literacy and technology self-efficacy independently explain digital financial services adoption among employees.

Two clear patterns emerge. First, trust is the strongest predictor of adoption. Second, technology self-efficacy also makes a meaningful positive contribution. By contrast, financial literacy does not have a statistically significant direct effect after trust and self-efficacy are considered simultaneously. The model nevertheless explains about half of the variance in DFS adoption, indicating that the three-construct framework captures a substantial portion of employee adoption behaviour. The positive effect of trust is consistent with the argument that digital finance creates a distinctive form of vulnerability. Users must rely on an interface, a provider and a technical infrastructure that they cannot fully observe. Under such conditions, trust reduces uncertainty and supports willingness to transact.

This finding aligns with electronic-commerce research that positions trust as an important complement to conventional technology-acceptance beliefs (McKnight et al., 2002; Gefen et al., 2003), mobile-payment evidence emphasizing consumer trust (Chandra et al., 2010), and mobile-banking studies identifying initial trust as a critical adoption condition (Zhou, 2011; Singh & Srivastava, 2018). It is also consistent with Indian evidence that trust relationships involving digital financial intermediaries affect participation in digital payments (Yadav & Kalluru, 2024). The present result shows that trust retains a strong unique effect even after financial capability and technology confidence are controlled.

Technology self-efficacy also has a significant positive effect, supporting social-cognitive reasoning. Efficacy beliefs influence whether individuals initiate behaviour, how much effort they exert and how persistently they respond to difficulty (Bandura, 1997). Employees who believe they can competently execute digital tasks are therefore more likely to adopt DFS because confidence reduces avoidance and increases persistence when interfaces or procedures appear unfamiliar. This result is consistent with the long-standing role of computer self-efficacy in technology use (Compeau & Higgins, 1995), cross-country mobile-banking evidence (Malaquias et al., 2021), and fintech research emphasizing digital technology self-efficacy (Lee, 2021). Importantly, self-efficacy is not simply a proxy for trust: the discriminant-validity results show that the constructs remain empirically distinct while both explain unique variance in DFSA. The non-significant financial-literacy path is the most theoretically interesting result. Prior research frequently finds that financial or digital financial literacy facilitates participation in digital finance (Kass-Hanna et al., 2022; Ravikumar et al., 2022; Yang et al., 2023; Pak et al., 2026). In the present model, financial literacy is positively correlated with DFSA, yet its direct path becomes negligible when trust and technology self-efficacy are entered simultaneously. Financial literacy is also relatively strongly associated with technology self-efficacy. This pattern suggests that financial knowledge may not provide substantial additional explanatory power for adoption once confidence in using technology is considered. Another possibility is that financial literacy matters more for the quality, complexity and consequences of digital financial choices than for basic adoption itself. Yang et al. (2023), for example, found stronger literacy effects for complex digital-finance activities than for routine mobile payments. The current result therefore indicates a weak incremental direct effect, not an absence of broader value from financial literacy.

The study makes three theoretical contributions. First, it separates assurance (trust), financial decision capability (financial literacy) and execution confidence (technology self-efficacy), showing that

trust and self-efficacy are not interchangeable. Second, the insignificant financial-literacy coefficient demonstrates the value of testing predictors jointly because a bivariate association may disappear after adjacent capabilities are controlled. Third, the findings support a differentiated view of digital financial capability in which knowledge, confidence and assurance have distinct behavioural consequences. The practical implications are equally clear. Financial-service providers should prioritize trust-building mechanisms that users can observe and understand. Transparent security practices, clear transaction confirmation, accessible grievance redressal, visible fraud-prevention measures, understandable privacy communication and dependable customer support can reduce uncertainty. Trust should be cultivated through the entire user journey rather than through promotional claims alone. For employers, banks and fintech firms, the results also support practical technology-confidence interventions. Short guided demonstrations, sandbox-style practice, step-by-step onboarding, accessible help functions and peer-support arrangements can create mastery experiences that strengthen self-efficacy. Training should therefore focus not only on what a financial product is but also on helping users successfully complete representative digital tasks.

The weak direct financial-literacy effect cautions against assuming that general financial education by itself will increase DFS adoption. Financial-literacy initiatives remain valuable, particularly for responsible borrowing, investment evaluation and fraud avoidance, but adoption programmes may be more effective when financial education is combined with hands-on digital practice and trust-enhancing safeguards. Several limitations should guide interpretation. First, the study is based on a sample of 200 employees, so replication with larger and more heterogeneous employee groups would strengthen external validity. Second, the model focuses on three direct antecedents and does not distinguish among specific DFS categories such as payments, banking, credit, insurance or investment platforms. Third, the constructs are measured through a common survey response format, which can introduce common-method variance even when measurement diagnostics are satisfactory. Fourth, the cross-sectional analytical design limits causal interpretation. Future studies should use multi-wave or longitudinal designs, incorporate behavioural usage records where feasible, distinguish basic adoption from sophisticated DFS usage, and evaluate whether the model is stable across demographic, occupational and service-category subgroups. Future research should also test whether financial literacy affects adoption indirectly through technology self-efficacy, perceived risk or trust; whether age, digital experience, income or occupational level moderate the paths; and whether the relationships differ across

banking, payments, credit and investment services. Cross-context studies could further determine whether the dominance of trust and self-efficacy is specific to employees or generalizes to self-employed, rural, older or financially vulnerable populations.

6. Conclusion

This study addressed the problem of explaining why employees differ in their adoption of digital financial services even when digital access is increasingly widespread. By integrating trust, financial literacy and technology self-efficacy in a single model, the research examined three conceptually different drivers of adoption: confidence in the provider and system, capability to understand financial choices, and confidence in performing digital tasks. The findings provide a clear answer to the research objective. Trust and technology self-efficacy emerge as the principal direct drivers of DFS adoption, while financial literacy does not make an independent direct contribution once the other two factors are taken into account. The results therefore suggest that adoption is shaped more strongly by whether employees believe a digital financial environment is dependable and whether they feel capable of using it than by financial knowledge alone. This does not diminish the broader importance of financial literacy; rather, it indicates that financial knowledge may be more consequential for the quality and sophistication of financial decisions than for the initial act of adopting digital services. The study contributes theoretically by distinguishing assurance, knowledge and self-efficacy within one parsimonious framework and by showing that these factors have unequal explanatory roles. Practically, it indicates that financial institutions and employers should complement financial education with visible trust-building measures and hands-on digital capability development. Clear safeguards, responsive support and opportunities to build successful experience with digital tools are likely to be central to stronger adoption. Overall, the study reinforces a simple but important principle: expanding digital finance requires more than making technology available. Sustainable adoption depends on users being able to trust the system and trust their own ability to use it. Future research that adds behavioural usage data, richer sampling information and indirect or moderating mechanisms can build on this framework to explain not only whether employees adopt DFS, but also how confidently, safely and effectively they continue to use them. For managers and policy-oriented stakeholders, this means that adoption strategies should be judged by whether they reduce uncertainty and build user mastery, not simply by how many digital features or educational messages they provide.

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