The Role of AI Literacy and Financial Literacy on Fintech Adoption: Pathway toward Financial Inclusion

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Abstract

Financial inclusion has become a strategic priority for emerging economies, with financial technology (Fintech) offering new avenues to overcome long-standing barriers to formal financial access. In Vietnam, small and medium enterprises (SMEs) play a pivotal role in economic growth yet continue to experience persistent financing constraints. This study investigates the determinants of Fintech adoption and its contribution to financial inclusion at the firm level. Drawing on the Technology Acceptance Model and extending it with cognitive and institutional dimensions, a comprehensive framework is proposed that integrates AI literacy, financial literacy, government support, perceived ease of use, perceived usefulness, and trust as key antecedents. Data from 568 Vietnamese enterprises across multiple sectors were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that perceived ease of use and perceived usefulness are the most influential drivers of Fintech adoption, while AI literacy and financial literacy significantly enhance both adoption and inclusion. Government support and trust further strengthen adoption, emphasizing the importance of regulatory stability and security assurance. The study enriches theoretical understanding by integrating capability-based, perception-based, and institutional perspectives, while offering practical guidance for policymakers, firms, and Fintech providers seeking to advance inclusive digital finance in emerging markets.

Research purpose:

This study investigates the role of AI literacy, financial literacy, government support, perceived ease of use, perceived usefulness, trust and security risk in shaping Fintech adoption and its impact on financial inclusion among Vietnamese SMEs.

Research motivation:

Despite the rapid expansion of Vietnam's digital economy, financial inclusion remains uneven, with SMEs facing significant barriers to affordable finance. While prior research emphasizes consumer-level adoption, firm-level determinants remain underexplored. This study addresses this gap by extending the Technology Acceptance Model with capability-based and institutional factors.

Research design, approach, and method:

A survey of 568 Vietnamese firms was conducted, covering diverse industries, ownership types, and regions. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), enabling assessment of both measurement and structural models with direct and mediated effects.

Main findings:

Perceived ease of use and perceived usefulness emerged as the most influential drivers of Fintech adoption, confirming that usability and performance expectations remain central to technology acceptance. AI literacy and financial literacy also exerted significant positive effects on both adoption and financial inclusion, emphasizing the role of cognitive capabilities in enabling digital transformation. Government support and trust further reinforced adoption by providing institutional stability and enhancing user confidence, while perceived security risk negatively affected adoption, reflecting ongoing concerns about data protection and privacy.

Practical/managerial implications:

The findings highlight the need for firms to prioritize user-friendly and value-adding fintech platforms, invest in AI and financial literacy training, and ensure robust trust mechanisms. Policymakers should enhance regulatory support and digital infrastructure to accelerate inclusive finance through Fintech adoption

Keywords: AI literacy, financial literacy, Fintech adoption, financial inclusion, SMEs.

1. INTRODUCTION

Financial inclusion has been increasingly acknowledged as a critical foundation of sustainable economic development,

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especially in the aftermath of global financial crises that exposed deep inequalities in access to formal financial services. According to the World Bank's Global Findex Database 2025 (Klapper et al., 2025), affordable and reliable access to financial services not only improves household welfare but also enables small and medium enterprises to expand operations and mitigate risks. In line with this perspective, the United Nations has incorporated financial inclusion into several Sustainable Development Goals (SDGs), including poverty reduction, gender equality, and narrowing inequality both within and across countries. These policy initiatives highlight that inclusive financial systems are essential for resilience, entrepreneurship, and shared prosperity. Despite significant progress, disparities persist. The Global Findex 2025 reports that 79 percent of adults worldwide owned a financial account in 2024, compared to 51 percent in 2011. In low and middle income economies, account ownership reached 75 percent, driven by digital payments and mobile money services. However, nearly 1.3 billion adults worldwide still lack access to a financial account, with the majority concentrated in low and middle income economies. Women, rural residents, and low income households remain disproportionately excluded. The gender gap in account ownership has narrowed but continues to exist in developing economies. Additional barriers, including weak financial literacy, limited trust in financial institutions, and the cost and complexity of documentation, further constrain inclusive access (World Bank, 2025).

Vietnam provides a particularly relevant case for discussions on financial inclusion and digital transformation. As one of the fastest growing digital economies in Southeast Asia, the country has witnessed rapid advances in internet penetration, mobile connectivity, and digital payment systems. The government has identified digital transformation as a central pillar of economic development, as emphasized in Decision No. 749/QD-TTg (2020) which approved the National Digital Transformation Program. Nevertheless, financial inclusion remains incomplete. According to estimates from the State Bank of Vietnam and the World Bank, a large proportion of the population, especially in rural and remote regions, continues to be excluded from the formal financial system. Small and medium enterprises, representing over 97 percent of Vietnamese firms and contributing more than 45 percent of GDP, also face difficulties in accessing affordable finance. Expanding financial inclusion is therefore both an economic necessity and a strategic priority for Vietnam's digital future. The emergence of financial technology (Fintech) offers a transformative pathway for addressing these barriers. Fintech applications draw on digital innovations to deliver financial services such as mobile payments, peer to peer lending, crowdfunding, blockchain based transactions, robo advisory platforms, and AI supported credit scoring (Lee and Shin, 2018). These services provide cost effective, accessible, and user friendly alternatives to conventional banking, particularly benefiting SMEs and individuals underserved by traditional institutions. The COVID 19 pandemic accelerated the shift toward digital adoption as firms and consumers increasingly relied on online platforms for financial activities. Evidence shows that fintech adoption not only improves operational efficiency for firms but also reduces transaction costs and extends financial services to excluded groups (Milian et al., 2019; Thakor, 2020). At the same time, fintech adoption contributes to inclusive growth by supporting marginalized communities such as women led businesses and rural households (Allen et al., 2016; Hasan et al., 2021). Collectively, these developments position fintech as a key enabler of Vietnam's long term socio economic development agenda.

Despite these opportunities, adoption remains uneven across sectors and regions. Empirical studies suggest that multiple factors influence firms' willingness and ability to adopt Fintech. Technology Acceptance Model (TAM) constructs, such as perceived ease of use and perceived usefulness, have been shown to significantly shape adoption behavior by influencing firms' perceptions of technology-related effort and benefits (Davis, 1989; Oliveira et al., 2016). Trust also emerges as a critical determinant, as businesses often hesitate to adopt financial technologies due to concerns about data security, fraud, and institutional reliability (Gao and Waechter, 2017; Alrawad et al., 2023). Beyond individual perceptions, institutional factors such as government support play an enabling role by reducing uncertainty, providing regulatory clarity, and fostering innovation ecosystems (Jahanmir and Cavadas, 2018; Senyo et al., 2024). In addition, cognitive capabilities such as financial literacy and AI literacy are increasingly important, as firms must not only access but also effectively evaluate and utilize digital financial tools (Lusardi and Mitchell, 2014; Wang et al., 2022). Together, these determinants shape the trajectory of Fintech adoption and its subsequent impact on financial inclusion.

While existing research has extensively examined Fintech adoption from the perspective of individual consumers, systematic analysis at the firm level remains limited, particularly in the case of small and medium-sized enterprises (SMEs) in Vietnam. This gap is striking, given that SMEs constitute the backbone of the Vietnamese economy and play a crucial role in advancing inclusive finance. Similar gaps have been noted in broader international contexts, where most studies have focused on consumer behavior rather than organizational adoption, despite evidence that firms' uptake of Fintech significantly shapes productivity, competitiveness, and market resilience (Gomber et al., 2018; Zavolokina et al., 2016). Moreover, prior research has often examined adoption drivers in isolation, such as technological readiness or regulatory support, without capturing the complex interplay between technological perceptions, organizational capabilities, institutional frameworks, and trust (Venkatesh et al., 2003; Claessens et al., 2018).

To address these limitations, our study develops and empirically tests an integrated research model that incorporates key antecedents of Fintech adoption. Fintech adoption is, in turn, hypothesized to enhance financial inclusion at the firm level by lowering transaction barriers and expanding access to affordable financial services. By situating the analysis within the rapidly digitizing Vietnamese economy while drawing on insights from international scholarship, this study

contributes to both the academic literature on technology adoption and the global policy discourse on financial inclusion.

Beyond theoretical contributions, the study also carries important practical relevance. Understanding how literacy, institutional support, and perception-based factors jointly shape adoption provides insights for policymakers, regulators, and Fintech providers seeking to improve inclusive digital finance. By highlighting SMEs as a focal point, the findings will inform strategies to reduce financial exclusion, promote equitable participation in the digital economy, and foster sustainable growth. Ultimately, this research not only enriches conceptual debates on technology acceptance and financial inclusion but also offers a timely roadmap for emerging economies such as Vietnam to leverage Fintech for broader socio-economic transformation.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Technology Acceptance Model

Davis (1989) proposed the TAM as a concise theoretical lens to understand how individuals adopt and use information technologies. The framework highlights two central perceptions: Perceived Usefulness (PU), which reflects the belief that a system can improve work outcomes, and Perceived Ease of Use (PEU), which refers to the extent to which a system is regarded as effortless to operate. These constructs explain how users form attitudes and intentions toward technology adoption, offering an essential basis for studying technology acceptance behavior (Davis, 1989).

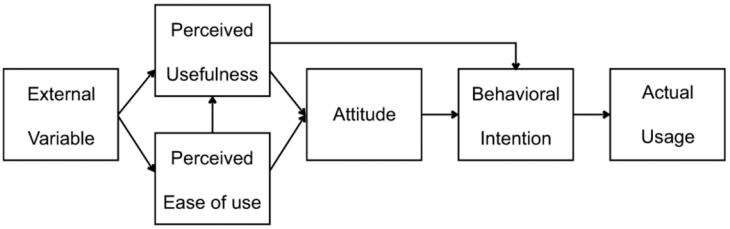

Figure 1. Technology Acceptance Model (TAM)

Sources: Davis (1989)

Later research expanded TAM by examining antecedents of these beliefs. Venkatesh (2000) argued that PEOU is influenced not only by system characteristics but also by psychological dimensions such as perceptions of control, intrinsic motivation, and emotional states. His findings suggest that ease of use reflects a combination of technical design and user affect, underscoring the multidimensional nature of technology adoption (Venkatesh, 2000). Building on this, Venkatesh and Bala (2008) developed TAM3, which integrated social influence, user experience, and facilitating conditions as determinants of PU and PEOU. They further emphasized that interventions such as training programs and redesign of systems can directly shape users' perceptions of usefulness and ease of use, thereby increasing the likelihood of technology adoption (Venkatesh and Bala, 2008). TAM provides a robust and validated theoretical basis for analyzing user adoption of digital innovations. By grounding adoption in the dual constructs of PU and PEOU, TAM helps explain why users engage with emerging technologies (Davis, 1989; Venkatesh, 2000; Venkatesh and Bala, 2008).

2.2. Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) with the goal of consolidating diverse approaches to technology acceptance. This framework was synthesized from eight earlier models, including the Technology Acceptance Model and the Theory of Planned Behavior. UTAUT identifies four major factors that shape behavioral intention and the actual use of technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the belief that using a technology will improve individual outcomes, while effort expectancy concerns the degree of perceived simplicity in its use. Social influence reflects the pressure exerted by significant others to adopt a system, and facilitating conditions describe the organizational and technical support available for use. Together, these dimensions provide a robust and comprehensive explanation of variations in technology adoption (Venkatesh et al., 2003).

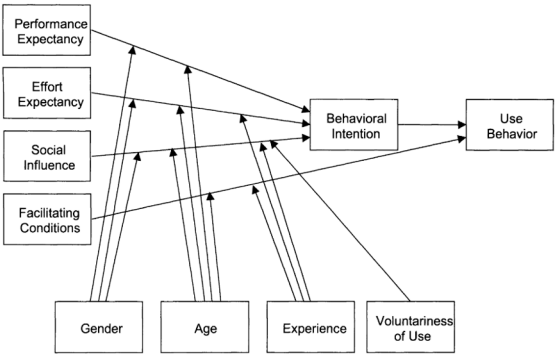

Figure 2. Unified Theory of Acceptance and Use of Technology (UTAUT)

Sources: Venkatesh et al., 2003

Recognizing the increasing role of consumers in digital environments, Venkatesh et al. (2012) extended the model into UTAUT2, adapting it for consumer contexts. UTAUT2 introduced constructs such as hedonic motivation, price value, and habit, thereby broadening explanatory power and enhancing prediction of technology use in non-organizational settings (Venkatesh et al., 2012). This extension was particularly important for understanding consumer adoption of emerging technologies, where factors such as enjoyment, cost-benefit trade-offs, and habitual behaviors are central drivers. A decade later, Venkatesh et al. (2016) provided a synthesis of UTAUT research, evaluating its global application and outlining future directions. They emphasized that UTAUT has been widely validated across industries and cultures, but also highlighted the importance of contextual adaptation and integration with emerging constructs such as trust and risk in digital technology adoption (Venkatesh et al., 2016). These contributions confirm that UTAUT and its extensions offer a robust foundation for analyzing fintech adoption, where performance benefits, ease of use, social influences, and consumer-specific factors jointly shape behavioral intentions and usage behaviors (Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016).

2.3. AI Literacy

AI literacy has recently been recognized as a critical construct in the digital economy, capturing individuals' ability to understand, interact with, and effectively use AI systems (Ng et al., 2021; Wang et al., 2022). Ng et al. (2021) conceptualized AI literacy as a multidimensional competence that includes knowledge of AI concepts, awareness of its applications, critical evaluation of AI systems, and ethical considerations in their use. Building on this conceptualization, Wang et al. (2022) developed and validated an AI literacy scale that emphasizes user competence in applying AI-based tools, highlighting its importance for enabling individuals to navigate AI-driven environments with confidence. These definitions indicate that AI literacy extends beyond technical knowledge to include awareness, critical thinking, and practical application, all of which influence how individuals interact with emerging digital technologies (Ng et al., 2021; Wang et al., 2022).

Recent research has further highlighted the role of AI literacy in shaping technology adoption behaviors. Akhtar et al. (2024) found that AI knowledge combined with financial service competence significantly enhances user innovativeness and willingness to adopt fintech solutions, with government support and user creativity reinforcing these effects. Similarly, Ikhsan et al. (2025) confirmed that AI adoption in the Indonesian banking sector was strongly associated with ease of use, trust, and perceptions of reliability. Their findings suggest that individuals with higher AI literacy are more likely to recognize the benefits of fintech platforms and to perceive them as accessible and reliable. Moreover, Vuković et al. (2025), through a systematic review, emphasized that successful integration of AI in financial services requires not only institutional and regulatory readiness but also an informed user base capable of leveraging technological innovations.

Hypothesis 1 (H1): AI literacy positively influences Fintech adoption.

2.4. Financial Literacy

Financial literacy is generally described as the knowledge and capability to apply financial concepts in order to make sound decisions and improve individual financial well being (Huston, 2010). Lusardi and Mitchell (2014) emphasized that financial literacy encompasses understanding financial products and the ability to apply this knowledge for long term planning, saving, and money management, thereby linking it to broader economic behavior. More recent

definitions highlight that financial literacy is not limited to factual knowledge but also includes behavioral attitudes and confidence, while acknowledging that overconfidence can sometimes undermine actual financial well being (Vörös et al., 2021). Overall, financial literacy is now viewed as a multidimensional construct that integrates cognitive understanding, practical skills, and behavioral components relevant to personal finance (Huston, 2010; Lusardi and Mitchell, 2014; Vörös et al., 2021).

Empirical studies consistently show that financial literacy plays an important role in technology adoption, particularly within financial technology. Akhtar et al. (2024) found that knowledge of financial services, as part of financial literacy, positively affects user innovativeness and intention to adopt fintech platforms, with AI related factors and government support further reinforcing this relationship. AlSuwaidi and Mertzanis (2024) also reported global evidence that financial literacy strongly predicts the growth of fintech markets, suggesting that financially literate consumers are more likely to use and trust fintech services. This implies that financial literacy reduces informational barriers and strengthens confidence in adopting financial technologies. Grohmann et al. (2018) provided cross country evidence that higher levels of financial literacy are linked to greater access to and use of formal financial services, especially in developing economies.

Hypothesis 2 (H2): Financial literacy positively influences Fintech adoption.

2.5. Government Support

Government support is generally understood as the provision of policies, resources, and institutional mechanisms that enable organizations to innovate, adapt, and sustain performance in dynamic environments (Igalla et al., 2019). Such support includes financial incentives, regulatory frameworks, and infrastructural initiatives that reduce uncertainty, mitigate risks, and lower barriers to technological adoption (Prasannath et al., 2024). Nast et al. (2024) further argued that these measures act as catalysts for technological advancement by fueling research, development, and diffusion across industries. This view is consistent with diffusion of innovation theory, which emphasizes that external support mechanisms can either accelerate or hinder adoption depending on how effectively they address organizational concerns and structural constraints (Jahanmir and Cavadas, 2018). Within fintech ecosystems, government initiatives have been shown to be particularly influential in shaping adoption. Senyo et al. (2024) highlighted that regulatory sandboxes and digital transformation policies provide firms with safe environments to experiment, reduce institutional risks, and build trust among stakeholders. Supportive interventions also enhance entrepreneurial orientation and SME performance, indicating that government policies directly influence organizational innovation capacity and adoption decisions (Prasannath et al., 2024).

Hypothesis 3 (H3): Government support positively influences Fintech adoption.

2.6. Perceived Ease of Use

Perceived Ease of Use (PEU) is a central construct in the TAM defined as the extent to an organization believes that applying a particular system will be free of effort (Davis, 1989). In the enterprise context, PEU reflects the degree to which managers and employees perceive that a digital solution can be adopted without excessive training, integration costs, or disruption to existing workflows. This perspective highlights that technology adoption within firms is not only influenced by its expected benefits but also by the cognitive and operational effort required for effective implementation (Davis, 1989). Venkatesh (2000) demonstrated that perceptions of ease are shaped by both technical design features and organizational factors such as perceived control, intrinsic motivation of employees, and the reduction of anxiety during implementation. In the fintech domain, empirical evidence confirms that PEU is a critical driver of adoption at the organizational level. Oliveira et al. (2016) showed that firms considered mobile payment systems more adoptable when they were simple, clear, and seamlessly integrated into business operations, which positively influenced adoption and recommendation intentions. Liébana-Cabanillas et al. (2018) also found that PEU significantly reduced uncertainty and enhanced organizational confidence in adopting mobile payment systems, indicating that simplicity is a decisive factor in enterprise-level decisions. More recently, Belanche et al. (2022) highlighted that while perceived risks in peer-to-peer payment systems may hinder adoption, PEU mitigates these concerns by reducing complexity, thereby making fintech platforms more accessible for firms.

Hypothesis 4 (H4): Perceived ease of use positively influences Fintech adoption.

2.7. Perceived Usefulness

Perceived Usefulness (PU) refers to the extent to which a person believes that the use of a particular system will enhance their performance and effectiveness (Davis, 1989). Within the framework of the Technology Acceptance Model, PU captures the practical value of technology by emphasizing that individuals are more willing to adopt innovations when they expect tangible benefits such as greater efficiency, convenience, or improved outcomes (Davis, 1989). A considerable body of empirical research confirms the central importance of PU in organizational technology adoption. For instance, Oliveira et al. (2016) observed that mobile payment systems are regarded as useful by firms when they enable faster, safer, and more cost effective transactions, which subsequently shape adoption and recommendation

behavior. Similarly, Zhou (2012) noted that the usefulness of mobile financial services, together with organizational mobility and routines, significantly drives adoption decisions. Expanding this argument, Gong et al. (2020) demonstrated that PU not only influences adoption but also contributes to satisfaction after adoption, as firms consider whether fintech solutions improve service delivery and customer management.

Hypothesis 5 (H5): Perceived usefulness positively influences Fintech adoption.

2.8. Perceived Trust

Trust is widely recognized as a fundamental determinant of technology adoption, defined as the belief that a system or provider will act reliably, securely, and in the best interest of the adopter (Gao and Waechter, 2017). In the fintech context, trust reduces perceptions of uncertainty and risk, enabling firms to adopt new financial technologies with greater confidence (Zarifis and Cheng, 2022). Because digital transactions involve sensitive financial data, organizational decisions to implement fintech solutions are strongly conditioned by the extent to which these platforms are perceived as trustworthy (Gao and Waechter, 2017; Zarifis and Cheng, 2022). Yeboah et al. (2020) found that merchant adoption of mobile payments depended heavily on trust in service providers, particularly regarding data protection and transaction reliability. Similarly, Gao and Waechter (2017) demonstrated that initial trust strongly predicts adoption intentions for mobile payment services, suggesting that organizations often make early adoption decisions based on trust before accumulating usage experience. Talwar et al. (2020) further showed that trust continues to influence continuation intention after adoption, indicating that organizations' sustained engagement with fintech services relies on maintaining trust. More recently, Alrawad et al. (2023) confirmed that trust mitigates perceived risks in near-field communication payment systems, thereby strengthening adoption intentions among firms.

Hypothesis 6 (H6): Perceied trust positively influences Fintech adoption.

2.9. Perceived Security Risk

Perceived Security Risk (PSR) reflects users' concerns about potential losses stemming from privacy violations, unauthorized access or data breaches in FinTech systems (Wijaya et al., 2024). According to Johnson et al. (2018), perceived privacy and security risks are key limitations to the adoption of mobile payment services, as they directly undermine user confidence in digital transactions. Similarly, Elhajjar and Ouaida (2019) identified perceived risk as a critical deterrent to mobile banking adoption, while Sreejesh and Anusree (2016) confirmed that security and privacy concerns negatively shape customers' attitudes and intentions in online banking contexts. More recent studies also reinforce that users' perceptions of security strongly influence their trust and overall acceptance of FinTech solutions (Hidayat-ur-Rehman et al., 2025). In emerging markets, where cybersecurity literacy and regulatory enforcement remain limited, heightened perceptions of security risk can create psychological barriers that inhibit FinTech adoption (Singh et al., 2020).

Hypothesis 7 (H7): Perceied security risk negatively influences Fintech adoption.

2.10. Fintech Adoption and Financial Inclusion

Fintech adoption reflects the readiness of firms to embrace financial technologies that transform the delivery of financial products and services (Singh et al., 2020). Existing research indicates that this process is influenced by both technological drivers and strategic considerations, as organizations pursue efficiency, transparency, and competitiveness in the context of digital finance (Milian et al., 2019). Fintech applications also reshape the structure of financial intermediation by decreasing dependence on conventional banking systems and fostering new avenues for value creation (Thakor, 2020). Alt et al. (2018) emphasized that the diffusion of fintech significantly changes industry dynamics, with companies increasingly integrating technologies such as blockchain, artificial intelligence, and mobile platforms into financial services. Lee and Shin (2018) further argued that adoption choices are shaped by ecosystem conditions, alignment with business models, and investment priorities, highlighting that fintech should be understood as a strategic capability rather than a simple tool.

Beyond efficiency gains, fintech adoption is increasingly recognized as a powerful driver of financial inclusion because it expands access to formal financial services for underserved households, small firms, and emerging markets (Allen et al., 2016; Alt et al., 2018; Gallego-Losada et al., 2023). Yang and Zhang (2022) demonstrated that digital finance adoption in China improved household consumption and broadened access to credit, savings, and insurance, showing that adoption has direct inclusionary effects on economic participation. At the global level, Allen et al. (2016) documented that the spread of formal financial accounts is essential for inclusive finance, and fintech accelerates this process by lowering entry barriers and transaction costs. Gallego-Losada et al. (2023) further revealed that the academic literature on digital financial inclusion consistently underscores the role of fintech as a bridge to reach previously excluded populations. Hasan et al. (2021) added that financial literacy amplifies the impact of fintech adoption on inclusive finance, suggesting that technology must be complemented by knowledge and capabilities to maximize inclusion outcomes.

Hypothesis 8 (H8): Fintech adoption positively influences financial inclusion.

Figure 3 illustrates the conceptual framework of the study. Drawing from the reviewed literature and theoretical foundations, this study proposes a conceptual model that integrates organizational capabilities, institutional support, and technology acceptance variables to explain FinTech adoption and its contribution to financial inclusion. Specifically, factors such as AI literacy, financial literacy, government support, perceived ease of use, perceived usefulness, trust, and perceived security risk are identified as the main determinants influencing how firms adopt FinTech solutions. FinTech adoption is subsequently hypothesized to promote financial inclusion by enhancing access to financial services and supporting inclusive growth. By integrating these dimensions, the proposed framework consolidates prior research findings into a comprehensive model that provides a strong basis for empirical analysis.

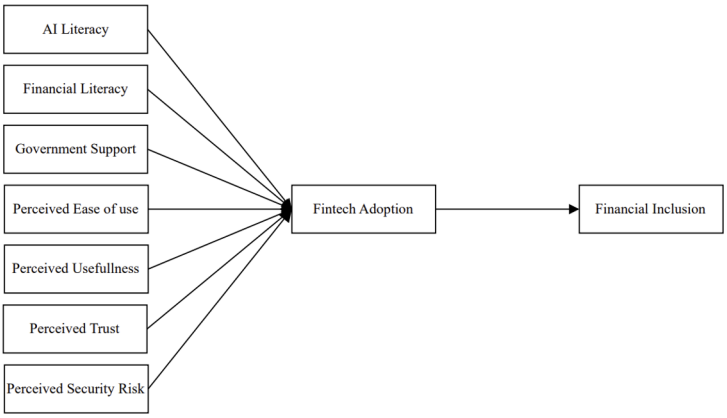

Figure 3. Conceptual Framework

3. METHODOLOGY

3.1. Research sample and data collection

The empirical data for this research were obtained through a structured survey distributed to firms operating in Vietnam. The purpose of the survey was to investigate the factors influencing fintech adoption and its contribution to financial inclusion. To capture a broad representation, a stratified sampling technique was applied to ensure variation in firm size, years of operation, ownership structure, and other relevant characteristics. Power analysis (Cohen, 1988) for a medium effect (f^2=0.15), α=0.05, and up to 8 predictors suggested a minimum of ~160 observations; our final sample of 568 firms exceeds this threshold, ensuring adequate statistical power for PLS-SEM.

Firms of varying sizes are well represented: 12.7% employ fewer than 50 employees, 16.1% employ between 50–100 employees, 31.6% fall within the range of 100–200 employees, and 39.6% have more than 200 employees. Regarding years of operation, 14.8% of firms have operated for less than five years, while 32.2% have operated for more than 20 years, indicating a balanced mix of young and established enterprises. Ownership structures are also diverse, with private enterprises accounting for the largest share (33.0%), followed by limited liability companies (22.7%), joint-stock companies (16.9%), state-owned enterprises (12.1%), foreign enterprises (9.3%), and partnerships (6.1%). In terms of geographical distribution, 49.6% of firms are located in Northern Vietnam, 17.6% in Central Vietnam, and 32.8% in Southern Vietnam. This stratified structure enhances the robustness of the study by capturing variations in firm characteristics and regional dynamics. The data collection process involved direct engagement with business owners and senior managers, ensuring that responses reflect organizational perspectives on fintech adoption and financial inclusion.

3.2. Construct measure

The constructs employed in this study include AI literacy, financial literacy, trust, perceived ease of use (PEU), perceived usefulness (PU), perceived security risk (PSR), government support, fintech adoption, and financial inclusion. These constructs were measured using validated multi-item scales adapted from prior literature. AI literacy items were taken from Wang et al. (2022), capturing firms' competence in understanding and applying AI technologies. Financial literacy was assessed using the framework developed by Lusardi and Mitchell (2014), which emphasizes knowledge and skills for effective financial decision-making. Trust was measured using scales from Alrawad et al. (2023) and Gao and Waechter (2017), reflecting confidence in fintech platforms and the reduction of risk perception. PEU and PU were operationalized using scales validated in the fintech context by Oliveira et al. (2016), Liébana-Cabanillas et al. (2018),

and Yen and Wu (2016). Perceived security risk (PSR) was measured using items adapted from Wijaya et al. (2024) and Johnson et al. (2018), capturing concerns about data breaches, privacy violations, and unauthorized access when using fintech applications. Government support was examined through items reflecting institutional and policy mechanisms as described in Jahanmir and Cavadas (2018) and Senyo et al. (2024). Fintech adoption was examined using items adapted from Lee and Shin (2018) and Aftab et al. (2025), while financial inclusion was measured following the framework of Pesqué-Cela et al. (2021). All measurement items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Minor revisions were made to improve clarity and contextual fit for enterprise respondents. The use of validated scales ensures reliability and validity, providing a solid basis for subsequent PLS-SEM analysis.

3.3. Data analysis

To test the research hypotheses, this study applied structural equation modeling with the partial least squares (PLS SEM) technique. PLS SEM has been widely recognized as a suitable method in business and management research, particularly when analyzing complex models and prediction-oriented studies (Hair et al., 2019; Hair et al., 2021). Unlike covariance-based approaches, PLS SEM does not rely on strict distributional assumptions and is appropriate for examining models with direct, mediating, and moderating effects. This feature makes it especially relevant for the multidimensional framework of this research, as it can handle both reflective and formative constructs while providing higher statistical power for medium sized samples (Cohen, 1988).

The measurement model was assessed following established guidelines for reliability and validity testing. Composite reliability values were examined to ensure they exceeded the recommended level of 0.70, indicating internal consistency. Convergent validity was confirmed when factor loadings were above 0.70 and the average variance extracted (AVE) was greater than 0.50 (Hair et al., 2019). Discriminant validity was evaluated using the heterotrait monotrait ratio (HTMT) suggested by Henseler et al. (2015), which is considered a more rigorous criterion than the traditional Fornell Larcker method.

After establishing the adequacy of the measurement model, the structural model was tested by examining path coefficients, significance levels, and explanatory power through the coefficient of determination (R^2). Bootstrapping with 10,000 resamples was employed to evaluate the statistical significance of the hypothesized relationships (Hair et al., 2021). In addition, the effect size (f^2) and predictive relevance (Q^2) were analyzed to strengthen the interpretation of results. All computations were conducted using SmartPLS version 4.0, which is specifically designed for variance based SEM applications.

4. RESULTS AND DISCUSSION

Table 1 presents the outer loadings of the observed indicators for the nine constructs, most indicators exhibit strong loadings well above the recommended threshold of 0.70 (Hair et al., 2019), confirming satisfactory indicator reliability. Specifically, AIL items range from 0.812 to 0.925, indicating excellent representation of the construct. FA items load between 0.805 and 0.926, while FIN items range from 0.803 to 0.911, all demonstrating high convergent validity. GS indicators (0.844–0.904) and PT items (0.849–0.912) also show strong internal consistency. PEU loadings vary from 0.769 to 0.924, and PU items from 0.765 to 0.921, both exceeding acceptable limits and reflecting stable measurement. PSR items exhibit loadings between 0.809 and 0.910, confirming adequate reliability. Only a few FL indicators (FL1–FL3) display relatively low loadings (0.408–0.455), suggesting limited explanatory strength for those specific items. Overall, the results provide strong evidence of convergent validity across constructs, indicating that the indicators are appropriately correlated with their respective latent variables. This confirms that the measurement model is well specified and suitable for subsequent structural analysis (Hair et al., 2019; Henseler et al., 2015).

Table 1. Outer loading

	AIL	DFL	FA	FIN	GS	PEU	PSR	PT	PU
AIL1	0.919								
AIL2	0.875								
AIL3	0.812								
AIL4	0.925								
FL1		0.408							
FL2		0.455							
FL3		0.433							

FL4	0.901								
FA1		0.926							
FA2		0.881							
FA3		0.805							
FA4		0.880							
FIN1			0.911						
FIN2			0.876						
FIN3			0.803						
FIN4			0.910						
FIN5			0.178						
FIN6			0.593						
GS1				0.904					
GS2				0.844					
GS3				0.874					
PEU1					0.910				
PEU2					0.924				
PEU3					0.881				
PEU4					0.769				
PSR1						0.869			
PSR2						0.910			
PSR3						0.809			
PSR4						0.866			
PT1							0.912		
PT2							0.886		
PT3							0.849		
PU1								0.765	
PU2								0.921	
PU3								0.886	
PU4								0.895	

Cronbach's alpha values range from 0.803 to 0.906 for most constructs, exceeding the recommended minimum of 0.70 according to Hair et al. (2019), which confirms internal reliability. The composite reliability coefficients rho a and rho c are all above 0.80, with most exceeding 0.90, indicating strong composite consistency. Average Variance Extracted values are higher than the acceptable threshold of 0.50 for all constructs except financial literacy, which records an AVE of 0.343, suggesting limited convergent validity for that construct. In contrast, the remaining constructs including

AIL, FA, FIN, GS, PEU, PSR, PT, and PU show satisfactory convergent validity with AVE values ranging from 0.547 to 0.781.

Table 2. Constructs reliability and convergent validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIL	0.906	0.913	0.934	0.781
FL	0.643	0.830	0.648	0.343
FA	0.896	0.903	0.928	0.764
FIN	0.803	0.863	0.865	0.547
GS	0.846	0.856	0.907	0.764
PEU	0.895	0.923	0.928	0.763
PSR	0.893	1.035	0.922	0.747
PT	0.860	0.881	0.914	0.779
PU	0.891	0.917	0.925	0.755

All HTMT values fall below the conservative threshold of 0.85 recommended by Henseler et al. (2015), confirming that each construct is empirically distinct from the others. The correlations among constructs remain moderate, indicating that no excessive overlap exists between latent variables. The lowest relationships are observed between perceived ease of use and the other constructs, suggesting that this factor is conceptually independent within the model. The relatively higher associations between AI literacy, financial inclusion, and fintech adoption are theoretically consistent, as firms with higher literacy levels are more likely to engage in financial technologies that promote inclusion.

Table 3. HTMT result

	AIL	DFL	FA	FIN	GS	PEU	PSR	PT	PU
AIL									
FL	0.546								
FA	0.483	0.327							
FIN	0.723	0.358	0.606						
GS	0.416	0.192	0.432	0.639					
PEU	0.154	0.133	0.167	0.205	0.227				
PSR	0.174	0.084	0.48	0.261	0.319	0.166			
PT	0.301	0.165	0.399	0.367	0.427	0.178	0.291		
PU	0.158	10.81	0.516	0.302	0.252	0.216	0.084	0.192	

4.2. Structural model

All VIF values range from 1.000 to 3.726, well below the conservative threshold of 5.0 (Hair et al., 2019), indicating no multicollinearity concerns among predictors. Regarding the structural paths, AIL → FA ($\beta = 0.175$, $p = 0.016$), FL → FA ($\beta = 0.141$, $p = 0.042$), FA → FIN ($\beta = 0.123$, $p = 0.039$), and GS → FA ($\beta = 0.158$, $p < 0.001$) are statistically significant, confirming their positive effects on fintech adoption and financial inclusion. PSR → FA ($\beta = -0.114$, $p = 0.005$) shows a significant negative effect, highlighting that higher perceived security risk reduces adoption

intentions. The paths PT → FA (β = 0.127, p = 0.056) and PU → FA (β = 0.100, p = 0.068) are marginally significant, while PEU → FA (β = 0.007, p = 0.822) is nonsignificant, suggesting that ease of use has limited influence within this model.

Table 4. Structural model results

	VIF	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIL -> FA	3.726	0.175	0.162	0.072	2.421	0.016
FL -> FA	3.451	0.141	0.156	0.069	2.035	0.042
FA -> FIN	1.000	0.123	0.536	0.044	2.083	0.039
GS -> FA	1.352	0.158	0.154	0.039	4.049	0.000
PEU -> FA	1.095	0.007	0.009	0.033	0.225	0.822
PSR -> FA	1.123	-0.114	-0.097	0.041	2.780	0.005
PT -> FA	1.230	0.127	0.189	0.056	2.274	0.056
PU -> FA	1.106	0.100	0.360	0.043	2.345	0.068

FA has an R^2 of 0.429 (adjusted R^2 = 0.422), indicating that approximately 42% of the variance in fintech adoption is explained by its predictors (AIL, FL, GS, PEU, PU, PSR, and PT). This represents a moderate level of explanatory power according to the criteria of Hair et al. (2019). Meanwhile, FIN records an R^2 of 0.286 (adjusted R^2 = 0.284), suggesting that fintech adoption accounts for nearly 29% of the variance in financial inclusion. These values confirm that the model demonstrates satisfactory predictive capability, with fintech adoption serving as an effective mediator linking literacy, support, and perception constructs to financial inclusion outcomes.

Table 5. R^2 and R^2 Adjusted result

Constructs	R Square	R Square Adjusted
FA	429	422
FIN	286	284

The f^2 values show that AIL (0.14), DFL (0.10), GS (0.32), PSR (0.20), PT (0.52), and PU (0.21) all exert meaningful effects on FA, while PEU (0.00) demonstrates a negligible impact. According to Cohen's (1988) and Hair et al.'s (2019) benchmarks, values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively. Accordingly, PT shows a large effect on FA, GS and PU exhibit moderate effects, and AIL, DFL, and PSR represent small to medium contributions. The f^2 value for FA → FIN (0.40) indicates a strong effect, confirming that fintech adoption substantially drives financial inclusion. These findings further reinforce the structural results, suggesting that fintech adoption is strongly shaped by multiple organizational and perceptual factors, and in turn, it serves as a key determinant of financial inclusion within the model (Cohen, 1988; Hair et al., 2021).

Table 6. Effect size result

	AIL	DFL	FA	FIN	GS	PEU	PSR	PT	PU
AIL			0.014						
FL			0.010						
FA				0.400					
FIN									
GS			0.032						

PEU	0.000
PSR	0.020
PT	0.052
PU	0.208

5. CONCLUSION

5.1. Theoretical implications

This study provides theoretical insights into the determinants of FA and its influence on FIN by integrating organizational capabilities, literacy constructs, and perception-based factors into a unified framework. The findings extend prior literature by confirming that both AIL and FL function as key enablers of digital financial transformation, highlighting the complementary roles of technological and financial knowledge in promoting fintech adoption. The positive and significant effects of PEU and PU further validate the relevance of the TAM in organizational fintech contexts, suggesting that perceived simplicity and perceived usefulness remain fundamental to adoption decisions even within complex enterprise environments.

The evidence also advances understanding of capability-based determinants. AIL and FL emerge as strong enablers of fintech adoption, indicating that both technological and financial competencies are critical for effective participation in the digital finance ecosystem. This theoretical linkage emphasizes that literacy constructs operate as foundational resources that shape organizations' readiness for digital transformation and indirectly promote FIN.

From a policy perspective, the role of GS is particularly critical. Regulatory clarity, sandbox initiatives, and digital infrastructure provided by the state can significantly lower uncertainty and promote adoption at the organizational level. Policymakers should therefore focus on creating stable regulatory environments and facilitating experimentation in safe conditions that encourage innovation.

Trust independently demonstrates a strong positive influence on FA, confirming its role as a trust-based mechanism underpinning digital technology acceptance. Trust enhances users' confidence in the reliability and integrity of fintech systems, serving as a counterbalance to perceived risk and a catalyst for sustained adoption.

5.2. Practical implications

This study provides several practical implications for managers, policymakers, and other stakeholders aiming to strengthen FA and enhance FIN. For managers, the findings underline the importance of focusing on PEU and PU when adopting fintech solutions. Firms should prioritize platforms that are easy to integrate, require minimal training, and deliver clear improvements in efficiency and performance. Simplifying system use and ensuring that digital tools demonstrate tangible business value can significantly reduce adoption resistance and enhance overall acceptance.

The results also emphasize the importance of capability development. AIL and FL both play critical roles in enabling effective fintech use and expanding financial inclusion. Organizations should invest in continuous training programs to enhance AI literacy and financial literacy among employees and managers. Strengthening these competencies helps firms build confidence in digital technologies, make informed financial decisions, and fully capitalize on emerging fintech opportunities.

From a policy standpoint, the influence of GS highlights the need for supportive institutional and regulatory environments. Policymakers should focus on promoting regulatory stability, offering sandbox mechanisms for safe experimentation, and improving national digital infrastructure. These initiatives can reduce uncertainty, encourage innovation, and accelerate the adoption of fintech across industries.

Trust also emerges as a vital factor in sustaining engagement with fintech systems. Firms should ensure that their fintech partners uphold strong security standards, maintain transparent governance, and establish credible reputations. Building and maintaining trust fosters confidence, reduces perceived risks, and encourages continued use of digital financial services.

5.3. Limitations and future research

While this study contributes to the understanding of fintech adoption and financial inclusion, several limitations remain. First, the data were collected from Vietnamese enterprises at a single point in time, which constrains causal inference and may not fully capture dynamic changes in fintech adoption and inclusion. Longitudinal or panel studies are therefore recommended to trace the evolution of adoption behaviors. Second, while the study focused on key constructs including ALI, FL, GS, PEU, PU, TRU and PSR, other relevant factors such as cost considerations, competitive pressures, cultural influences, or data governance readiness were not included and should be examined in future models. Third, the

analysis concentrated on Vietnam as an emerging market context, which may limit the generalizability of findings to other institutional environments. Comparative cross-country studies could reveal how regulatory maturity, digital infrastructure, or cultural differences shape adoption and inclusion pathways. Finally, the reliance on self-reported survey data introduces potential biases such as social desirability or perceptual overestimation. Future research could integrate multiple data sources, including financial performance metrics, platform usage data, or qualitative case studies, to strengthen triangulation and deepen insights. Addressing these limitations will help refine the theoretical model and broaden its applicability across different contexts.

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