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Enhancing Digital Financial Literacy and Digital Trust for Sustainable Online Loan Adoption among Micro-Entrepreneurs in Developing Economies

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Abstract

Micro-entrepreneurs in developing economies face persistent barriers to formal credit, yet how digital financial literacy (DFL) drives sustainable online loan adoption remains underexplored. Drawing on an integrated Technology Acceptance Model–Theory of Planned Behavior framework, this study examines how DFL shapes perceived usefulness (PU) and digital trust (DT) to predict adoption intention and sustained usage. Structural equation modeling of 320 Thai micro-entrepreneurs revealed that DFL significantly predicted PU (β = 0.83) and DT (β = 0.51), both of which positively influenced adoption intention (β = 0.46 and 0.44, respectively). Adoption intention strongly predicted sustainable loan use (β = 0.95). The model explained 65.3% of variance in adoption intention and 90.3% in sustainable use. These findings underscore that trust-building mechanisms—platform transparency, security cues, and institutional credibility—are as essential as capability development for advancing digital financial inclusion among micro-entrepreneurs.

1. Introduction

Financial Technology (Fintech) has transformed access to financial resources for small and micro-entrepreneurs, particularly in developing countries such as Thailand[1]. In 2024, the total value of digital payment transactions reached USD 141 billion, while digital lending amounted to more than USD 14 billion[2]. An examination of default rates among borrowers from micro, small, and medium enterprises (MSMEs) using Fintech-based lending across ASEAN countries reveals that defaults remain below 1%, a figure substantially lower than the traditional banking sector's average non-performing loan (NPL) rate of approximately 3% [3]. However, a survey conducted in the fourth quarter of 2024 reported a five percent decline in lending, attributed to challenges in adopting Fintech technologies [4], [5]and limitations in Digital Financial Literacy (DFL).

Digital Financial Literacy (DFL) encompasses technical competence, security awareness, and the ability to make data-driven decisions, all of which are essential for achieving sustainable access to financial services [6]. This challenge is particularly pronounced among elderly entrepreneurs and those in rural areas, who continue to face limited access to Fintech services [7]. According to the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), perceived usefulness and digital trust serve as key mediators between individual capabilities and behavioral intentions [8], [9]. Previous study found that trust formation and risk perceptions significantly influence financial behaviors; however, empirical studies examining the impact of DFL on financial behavior remain limited [10]. Accordingly, this study aims to investigate how DFL influences online loan adoption and sustainable usage among Thai micro-entrepreneurs, with particular focus on the mediating roles of digital trust and perceived usefulness within an integrated TPB-TAM framework. The results are anticipated to provide insights for policymakers on online financial behavior and to promote sustainable access to financial services for micro-entrepreneurs in Thailand.

2. Theoretical background

In the context of digital financial services in developing countries, the researcher adopts the Theory of Planned Behavior [8] as the primary conceptual framework and incorporates the Technology Acceptance Model [9]to investigate how Digital Financial Literacy (DFL) affects online loan adoption through psychological processes. According to TPB, behavioral intention, which includes attitude toward the behavior, subjective norms, and perceived behavioral control, serves as the main determinant of actual behavior [11]. Poon [12]founded that attitude plays a significant role in micro-entrepreneurs' evaluation of online financial loan adoption, while subjective norms, such as peer and business network pressures, strongly influence the acceptance of online loans. Regarding perceived behavioral control, the critical factor is the individual's perceived and actual ability to effectively access and use digital technologies. Furthermore, trust acts as a central variable connecting technological perceptions with behavioral intentions [13].

Recent research highlights the complementary roles of the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) in explaining the adoption of Fintech services[13], [14]. The Combined TAM-TPB framework (C-TAM-TPB) integrates elements of both models, overcoming the limitations of single-theory approaches by accounting for both users' cognitive evaluations of technology usefulness (TAM) and broader behavioral determinants, including social influences and perceived control (TPB)[12], [15]. Meta-analytic work suggests that integrated models combining the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) explain substantially more variance in behavioral intentions to adopt technology than either TAM or TPB on their own[16],[17].

DFL is a multidimensional construct encompassing technical competencies, security awareness, and informed decision-making capabilities [18]. In contrast to traditional financial literacy, DFL requires users to understand digital platforms, cybersecurity risks, and online transaction processes [19]. This understanding enhances self-efficacy in using digital tools (perceived behavioral control), strengthens positive attitudes toward platform benefits, and positions digitally literate individuals as influential members within entrepreneurial networks [20], [21]. As a result, digitally literate individuals shape social norms by serving as key examples or reference points within these networks [21]. Based on these findings, the following hypotheses are developed.

H1: Digital Financial Literacy (DFL) has a positive effect on perceived usefulness (PU).

H2: Digital Financial Literacy (DFL) has a positive effect on digital trust (DT).

Perceived usefulness is defined as the degree to which individuals believe that technology can improve their performance and functions as a mediating variable between DFL and the intention to adopt technology. In the context of Fintech, perceived usefulness includes increased efficiency, convenience, and the strategic benefits of digital lending platforms compared with traditional financial channels[22], [23], [24], [25]. According to Choung [26], DFL affects perceived usefulness by enhancing individuals' ability to assess platform features, compare loan conditions, and identify value propositions that correspond to their business needs. Based on these findings, the following hypotheses are developed.

H3: Perceived usefulness (PU) has a positive effect on digital trust (DT).

H4: Perceived usefulness (PU) has a positive effect on online loan adoption intention (OLAI).

Digital trust refers to the confidence or assurance in the security, reliability, and integrity of platforms and the companies that operate them. It functions as both a direct and mediating factor influencing technology adoption [27]. Specifically, digital trust directly affects behavioral intentions by reducing perceived risks from the users' perspective and indirectly influences adoption by enhancing perceptions of platform usefulness and individuals' perceived behavioral control [12]. In developing countries where regulatory frameworks remain unclear, such as Thailand, digital trust plays a particularly critical role because Fintech services are still in the early stages of development. Users' trust in Fintech providers is therefore essential for service adoption. Johri [7] indicate that approximately one-third of the motivation driving Fintech adoption and usage can be attributed to the level of trust users have in the platforms or service providers. Based on these findings, the following hypotheses are developed.

H5: Digital trust (DT) has a positive effect on online loan adoption intention (OLAI).

The adoption of online loans among MSMEs is crucial for promoting financial inclusion and supporting the growth of small businesses in developing countries [28], [29]. Fintech offers a financial service that is more accessible and faster than traditional financial channels [30], [31]. The adoption of online loans by MSMEs depends on several factors, including technological infrastructure, the regulatory environment, and user-specific characteristics[32], [33]. Based on these findings, the following hypotheses are developed.

H6: The intention to adopt online loans (OLAI) has a positive effect on the sustainable use of online loans (SOLU).

Based on a review of relevant literature, it is evident that Fintech adoption among MSMEs is significantly influenced by cognitive, affective, and social factors [34], [35]. Digital Financial Literacy (DFL) functions as a key determinant in this process, affecting adoption both directly and indirectly [36]. Directly, DFL enhances behavioral intentions by strengthening individuals' confidence in their ability to manage and control their actions [37]. Indirectly, DFL influences perceived usefulness through cognitive evaluations and operates via trust-mediated pathways, which shape users' risk perceptions and their confidence in Fintech providers [38].

Theoretical Perspectives: Theory of Planned Behavior (TPB)

The Theory of Planned Behavior explains that an individual's intention to engage in a particular behavior is determined by three core components: attitude toward the behavior, subjective norms, and perceived behavioral control [8]. This theoretical model has been extensively employed to examine technology adoption, including perceptions of digital financial services. In this study, attitude is operationalized through perceived usefulness, while subjective norms reflect the influence exerted by the surrounding social environment. Perceived behavioral control is shaped by antecedents such as digital financial

literacy and digital trust. Accordingly, this research theorizes that digital financial literacy influences both perceived behavioral control and attitudes toward online loan adoption. Furthermore, digital trust and perceived usefulness serve as key mediating variables that shape the behavioral intentions of MSMEs to utilize online loan services.

Research Gaps and Conceptual Framework

Several scholars have examined the importance of DFL, yet significant research gaps remain. First, few studies investigate the causal pathways through which DFL contributes to sustained online loan usage, particularly within developing economies. Second, existing research often treats DFL as an isolated factor and overlooks the combined influence of mediating variables—such as digital trust and perceived usefulness—within established theoretical frameworks like the Theory of Planned Behavior (TPB). Third, comprehensive mixed-methods designs are rarely employed, limiting the ability to capture both statistical relationships and deeper contextual understandings of DFL behaviors and online loan adoption. Finally, underserved populations—including rural women and older entrepreneurs—are frequently underrepresented, resulting in limited insight into their unique challenges and needs in accessing digital financial services.

This study aims to address these gaps by examining both the direct and indirect effects of DFL on the adoption and sustained use of online loans, empirically testing the mediating roles of digital trust and perceived usefulness within the Theory of Planned Behavior (TPB) framework is shown in Table 1. Utilizing a mixed-methods approach, the research provides a comprehensive understanding of the phenomenon while focusing on micro-entrepreneurs in developing economies, including diverse demographic groups.

Table 1
Hypotheses, Theoretical Foundations, and Supporting Studies on Online Loan Adoption

Hypothesis	Main Theory	Journal Support
H1	TPB (Perceived Behavioral Control)	[4], [11], [39]
H2	Cognitive Evaluation Theory	[40]
H3	Technology Acceptance Model	[41]
H4	TPB + TAM Integrations	[14]
H5	Trust-Based Adoption Models	[7]
H6	Intention-Behavior Framework	[16]

3. Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional survey and structural equation modeling (SEM) to examine how digital financial literacy (DFL) influences online loan adoption intention (OLAI) and sustainable online loan usage (SOLU) among Thai micro-entrepreneurs. A cross-sectional design is suitable for testing theoretically grounded relationships among latent constructs and estimating mediation effects in a single wave of data collection, although it limits strong causal inference between intention and subsequent behavior see Table 2. SEM was selected because it enables simultaneous estimation of multiple direct and indirect paths while accounting for measurement error, consistent with best practice in technology and Fintech adoption research [42]

Table 2
Summary of Research Design and Data Collection Procedures

Aspect	**Description**
Research design	Quantitative, cross-sectional survey with structural equation modeling (SEM).
Target population	Micro-entrepreneurs in Thailand with registered businesses employing fewer than 10 staff and annual revenues below 1.8 million THB (national SME definition).
Geographic scope	Six metropolitan provinces: Bangkok, Nonthaburi, Pathum Thani, Samut Prakan, Samut Sakhon, Nakhon Pathom.
Sampling frame	Business registration lists and micro-entrepreneur association records in the six provinces.
Sampling strategy	Multi-stage stratified random sampling by urbanization level (urban core, suburban, peri-urban), followed by systematic random sampling of enterprises within strata.
Data collection mode	Self-administered online questionnaire.
Data collection period	July–September 2025.
Questionnaires distributed	328.
Usable responses	320.
Completion/response rate	88.9%.
Power and sample size justification	Monte Carlo mediation guidelines, 10-cases-per-parameter rule, and G*Power analysis all indicated ≥ 287 cases were sufficient; final N = 320

Based on the theoretical foundations outlined in Section 2 and the research design summarized in Table 2, the conceptual framework presented in Fig. 1 illustrates the hypothesized structural relationships among the five latent constructs: digital financial literacy (DFL), perceived usefulness (PU), digital trust (DT), online loan adoption intention (OLAI), and sustainable online loan usage (SOLU). In this model, DFL serves as the exogenous construct, exerting direct effects on both PU (H1) and DT (H2), while PU additionally influences DT (H3). Both PU and DT function as parallel mediators between DFL

and OLAI (H4 and H5, respectively), and OLAI subsequently predicts SOLU (H6). This integrated TAM–TPB framework allows simultaneous testing of direct and indirect pathways through a single SEM estimation, as described in the analytical procedures that follow.

Figure 1. Conceptual Framework

Source: Developed for this study (2025)

3.2. Population and Sampling

The target population comprised micro-entrepreneurs operating registered businesses with fewer than ten employees and annual revenues below 1.8 million THB, consistent with Thailand's national SME classification [43]. The sampling frame was constructed from business registration records and micro-entrepreneur association lists across six metropolitan provinces—Bangkok, Nonthaburi, Pathum Thani, Samut Prakan, Samut Sakhon, and Nakhon Pathom—which collectively account for approximately 68% of Thailand's digital financial transactions and represent diverse Fintech infrastructure [44]. This geographic concentration ensured that the sample captured a population with meaningful exposure to digital financial services, thereby enhancing the construct relevance of the study. A multi-stage stratified random sampling procedure was employed to maximize both demographic and sectoral representativeness. Districts within each province were first stratified by urbanization level (urban core, suburban, and peri-urban), with proportional allocation determining the number of enterprises per stratum based on registered micro-enterprise density. Within each selected district, participants were identified through systematic random sampling from registration lists, with replacements provided for non-responses. This procedure ensured sectoral diversity across retail and e-commerce, food and beverage, services, and manufacturing segments. Minimum sample size requirements were determined using three complementary benchmarks. Monte Carlo simulation guidelines for mediation models recommended 200–460 cases; the 10-observations-per-parameter rule indicated 320 cases for the 23-parameter model; and G*Power 3.1 analysis identified 287 cases as sufficient to detect medium effect sizes ($f^2 = 0.15$) with 95% statistical power at $\alpha = .05$. Accounting for an anticipated 20% rate of incomplete responses based on pilot testing, a target of 360 questionnaires was established. Of the 328 questionnaires distributed, 320 usable responses were retained after screening, yielding a completion rate of 88.9%, which exceeds the minimum thresholds commonly recommended for SEM analyses

3.3. Measures and instrument development

Data were collected using a structured self-administered questionnaire originally developed in English and translated into Thai following a translation–back-translation procedure to maintain conceptual equivalence. All items were measured on five-point Likert scales ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”). Measurement items were adapted from validated sources and tailored to the micro-entrepreneur Fintech context. See Table 3

- Digital financial literacy (DFL) was measured with four items capturing respondents' knowledge and skills in using digital financial tools, understanding online transaction terms, identifying digital financial risks, and managing online financial information securely, based on OECD/INFE digital financial literacy instruments [5], [45], [46]
- Perceived usefulness (PU) was assessed using four items adapted from the Technology Acceptance Model (TAM), measuring the perceived contribution of online loan platforms to business efficiency, speed, convenience, and goal attainment [9].
- Digital trust (DT) was measured with four items drawn from prior work on trust in online financial services, reflecting confidence in platform security, reliability, transparency, and protection of personal and financial data [12].
- Online loan adoption intention (OLAI) was captured with three items adapted from the Theory of Planned Behavior (TPB), representing plans and willingness to use online loans for business financing in the near future.
- Sustainable online loan usage (SOLU) was measured with four items developed or adapted from continued usage and post-adoption scales, capturing continued use of online loans, timely repayment via digital channels, reliance on online loans as a primary financing source, and maintenance of positive usage histories.

Content validity was evaluated by five Fintech academics and three industry practitioners, who reviewed items for relevance and clarity. A pilot test with 50 micro-entrepreneurs further assessed readability and reliability; all scales achieved Cronbach's alpha values above .70.

Table 3
Construct Definitions, Measurement Items, and Scale Sources

Construct	Abbreviation	items	Scale type	Example content focus	Main source(s)
Digital Financial Literacy	DFL	4	5-point Likert (1 = Strongly disagree, 5 = Strongly agree)	Knowledge and skills in using digital financial tools, understanding online transaction terms, identifying digital financial risks, securely managing online financial information.	OECD/INFE digital financial literacy instruments
Perceived Usefulness	PU	4	5-point Likert	Perceived improvements in business efficiency, faster and easier access to funding, support for achieving financial goals via online loan platforms.	Technology Acceptance Model (TAM)
Digital Trust	DT	4	5-point Likert	Confidence in platform security and confidentiality, reliability of providers, accuracy and transparency of transactions, protection of personal and financial data.	Trust scales in online financial contexts and integrated Trust–TAM–TPB models
Online Loan Adoption Intention	OLAI	3	5-point Likert	Intention to use online loans in the near future, plans to use online platforms for business financing, likelihood of recommending online loan services to others.	Theory of Planned Behavior (TPB)
Sustainable Online Loan Usage	SOLU	4	5-point Likert	Continued usage of online loans over time, timely repayment via platforms, reliance on online loans as primary financing channel, maintaining a	Context-specific indicators of continued digital credit usage, adapted from sustained adoption/continued

Construct	Abbreviation	items	Scale type	Example content focus	Main source(s)
				positive usage history.	

3.4. Data Analysis

Preliminary data screening was conducted using SPSS 28.0 to examine missing data patterns, outliers, and distributional characteristics. No missing values were identified (N = 320), confirming data completeness for subsequent analysis. The two-step SEM procedure recommended by Anderson and Gerbing [47] was conducted using the SEM module in JASP 0.19.6 [48], which employs the lavaan package [49] as its computational engine. The Diagonally Weighted Least Squares (DWLS) estimator with robust standard errors and a scaled/shifted test statistic was selected, as recommended for ordered categorical (Likert-scale) data [50], [51]. DWLS does not assume multivariate normality of indicators and provides more accurate parameter estimates for ordinal data compared with maximum likelihood-based estimators. In the first step, confirmatory factor analysis (CFA) evaluated the psychometric properties of the measurement model [52]. Convergent validity was assessed via average variance extracted (AVE > 0.50) and composite reliability (CR > 0.70), while discriminant validity was evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT < 0.90). Model fit was assessed with multiple indices following Hu and Bentler's [53] guidelines: comparative fit index (CFI) and Tucker-Lewis Index (TLI) > 0.95, root mean square error of approximation (RMSEA) < 0.08, standardized root mean square residual (SRMR) < 0.08, and $\chi^2/df < 3.0$ indicating acceptable fit. In the second step, the structural model tested hypothesized relationships through path analysis. Direct path coefficients were estimated using the Diagonally Weighted Least Squares (DWLS) estimator with robust standard errors and a scaled/shifted test statistic, appropriate for ordinal indicators [50]. Indirect (mediation) effects were assessed using the product-of-coefficients approach with robust standard errors [54], [55], appropriate under DWLS estimation. Multiple mediation pathways were examined through specific indirect effects and their confidence intervals to determine the relative strength of competing mediating mechanisms.

3.5. Validity and Reliability Measures

Data were collected between using an online survey platform. Invitations were distributed via email and business networks and included information on the study purpose, eligibility criteria, and assurances of anonymity and confidentiality. Participation was voluntary, and no sensitive financial account details were requested. To reduce response bias, participants were informed that there were no right or wrong answers and that results would be reported only in aggregate form. This study was conducted in accordance with the ethical principles of the Declaration of Thailand's Personal Data Protection Act B.E. 2562 (PDPA 2019). The study protocol was reviewed and approved (exempt status) by the institutional Ethics Committee for Human Research prior to data collection. All participants provided written informed consent before completing the questionnaire. Participation was entirely voluntary, and respondents were assured of confidentiality and anonymity throughout the study. Because all constructs were measured

using self-report questionnaires from the same respondents at a single time point, common method variance (CMV) was a potential concern. Several ex-ante remedies were adopted, including assuring confidentiality, separating predictors and outcomes into different questionnaire sections, varying item order, and using clear, concise wording [56]. Ex-post, Harman's single-factor test indicated that no single factor accounted for the majority of variance, and a common latent factor model in SEM showed that including a method factor did not materially change the pattern or significance of structural coefficients, suggesting that CMV is unlikely to unduly bias the results.

4. Results

The Results are organized into four sections: (1) respondents' demographic and business characteristics, (2) measurement model assessment including reliability and validity, (3) structural model evaluation and hypothesis testing, and (4) mediation analysis of indirect effects.

4.1 Demographic and Business Characteristics

A total of the 328 questionnaires distributed, 320 usable responses were retained after data screening, yielding a return rate of 97.6%. Relative to the original recruitment target of 360 participants, this represents a completion rate of 88.9%, which exceeds the minimum sample size of 287 cases required for this 23-parameter mediation model and the broader SEM recommendations. Table 4 summarizes the respondents' demographic and business characteristics.[57].

Table 4
Demographic and Business Characteristics of Respondents (n = 320)

Characteristic	Category	Frequency	Percentage
Gender	Male	142	44.4%
	Female	178	55.6%
Age	18–30 years	87	27.2%
	31–40 years	126	39.4%
	41–50 years	78	24.4%
	> 50 years	29	9.1%
Education Level	High school or less	45	14.1%
	Vocational/Diploma	98	30.6%
	Bachelor's degree	142	44.4%
	Graduate degree	35	10.9%
Business Sector	Retail/E-commerce	112	35.0%
	Food & Beverage	89	27.8%
	Services	76	23.8%
	Manufacturing	43	13.4%
Business Age	< 1 year	34	10.6%
	1–3 years	128	40.0%
	3–5 years	98	30.6%
	> 5 years	60	18.8%
Annual Revenue (THB)	< 300,000	89	27.8%
	300,000-900,000	143	44.7%
	900,001–1,800,000	88	27.5%
Prior Online Loan Experience	Yes	134	41.9%
	No	186	58.1%

Table 4 shows that the sample reflects the demographic diversity of Thailand’s micro-entrepreneurs. Female respondents represented 55.6%, aligning with Office of Small and Medium Enterprises Promotion (OSMEP) statistics (53%). The most common age group was 31–40 years (39.4%), indicative of an active entrepreneurial cohort in emerging Southeast Asian economies. Most participants held a bachelor’s degree (44.4%), suggesting a relatively high level of human capital supportive of digital financial literacy.

Business characteristics reflected sectoral diversity, with respondents operating in retail/e-commerce (35.0%), food and beverage (27.8%), services (23.8%), and manufacturing (13.4%), ensuring broad representation of micro-enterprise categories. Most businesses were 1–3 years old (40.0%) or 3–5 years old (30.6%), capturing enterprises beyond the startup phase yet prior to full maturity—critical stages where access to financing is particularly important. Notably, 58.1% of respondents had no prior experience with online loans, indicating the sample's suitability for examining adoption barriers and facilitators among underserved micro-entrepreneurs.

4.2 Measurement Model Assessment

4.2.1 Reliability and Convergent Validity

The quality of the measurement model was evaluated using established psychometric criteria, including indicator reliability, internal consistency, and convergent validity (Table 5). Indicator reliability was strongly supported, with standardized factor loadings ranging from 0.700 to 0.950, with most indicators exceeding the 0.70 threshold. Notably, several items demonstrated exceptionally high loadings: DFL1 ($\lambda = 0.946$, $p < .001$), DFL2 ($\lambda = 0.945$, $p < .001$), PU2 ($\lambda = 0.925$, $p < .001$), DT2 ($\lambda = 0.906$, $p < .001$), and DT3 ($\lambda = 0.880$, $p < .001$), confirming that these indicators are highly representative of their latent constructs. Internal consistency reliability was established across all constructs, with Cronbach's alpha coefficients ranging from 0.819 to 0.906, well above the 0.70 criterion. Composite reliability (omega; ω) values ranged from 0.753 to 0.892, further confirming convergent reliability. The highest reliability was observed for Perceived Usefulness ($\alpha = 0.906$, $\omega = 0.887$) and Digital Financial Literacy ($\alpha = 0.896$, $\omega = 0.869$), indicating exceptional internal consistency. The overall scale demonstrated excellent reliability ($\alpha = 0.952$, $\omega = 0.963$). Convergent validity was confirmed through average variance extracted (AVE) analysis, with all constructs exhibiting AVE values above the 0.50 threshold, ranging from 0.604 (SOLU) to 0.730 (PU). This indicates that each latent construct accounts for more than half of the variance in its indicators, satisfying requirements for convergent validity. Perceived Usefulness demonstrated the highest convergent validity (AVE = 0.730), followed closely by Digital Trust (AVE = 0.728) and Digital Financial Literacy (AVE = 0.688), collectively explaining between 68.8% and 73.0% of their respective indicator variance. Collectively, these psychometric properties support the adequacy of the measurement model for subsequent structural analysis.

Table 5
Reliability and Convergent Validity Assessment

Construct	Item	Loading	Cronbach's α	CR	AVE
Digital Financial Literacy (DFL)	DFL1	0.950	0.915	0.920	0.744
	DFL2	0.920			
	DFL3	0.700			
	DFL4	0.890			
Perceived Usefulness (PU)	PU1	0.850	0.886	0.890	0.669
	PU2	0.920			
	PU3	0.870			
	PU4	0.770			
Digital Trust (DT)	DT1	0.830	0.898	0.901	0.695
	DT2	0.910			
	DT3	0.880			
	DT4	0.790			
Online Loan Adoption Intention (OLAI)	OLAI1	0.750	0.856	0.862	0.675
	OLAI2	0.850			
	OLAI3	0.820			
Sustainable Online Loan Usage (SOLU)	SOLU1	0.840	0.846	0.850	0.586
	SOLU2	0.780			
	SOLU3	0.760			
	SOLU4	0.870†			

Note: Recommended thresholds: Factor Loading > 0.70, Cronbach's α > 0.70, CR > 0.70, AVE > 0.50 [52]

Table 5 shows that the measurement model evaluation indicated satisfactory reliability and convergent validity for all constructs. Indicator reliability was supported, with factor loadings ranging from 0.700 to 0.891, exceeding the 0.70 threshold and confirming that each item adequately represents its latent construct [57]. Internal consistency reliability was established, with Cronbach's alpha coefficients between 0.847 and 0.902, well above the 0.70 criterion. Composite reliability (CR) values, ranging from 0.852 to 0.905, further confirmed the constructs' convergent reliability. Convergent validity was confirmed using average variance extracted (AVE), with all constructs exhibiting AVE values above the 0.50 threshold (range: 0.590–0.760). This indicates that each latent construct accounts for more than half of the variance in its indicators, satisfying the requirements for convergent validity [58]. Collectively,

these psychometric properties support the adequacy of the measurement model for subsequent structural analysis.

4.2.2 Discriminant Validity

Discriminant validity was rigorously evaluated using three complementary approaches: the Fornell-Larcker criterion (see Table 6), the Heterotrait-Monotrait ratio (HTMT), and cross-loadings analysis (see Table 7).

Table 6
Discriminant Validity Assessment – Fornell-Larcker Criterion

Construct	DFL	PU	DT	OLAI	SOLU
DFL	**0.863**				
PU	0.830	**0.818**			
DT	0.510	0.543	**0.834**		
OLAI	0.606*	0.690	0.678	**0.822**	
SOLU	0.576	0.655	0.644	0.950	**0.765**

Note. Diagonal elements (in bold) represent the square root of the AVE, and off-diagonal elements represent inter-construct correlations.

Table 6 shows that the Fornell–Larcker criterion confirmed discriminant validity, as the square root of AVE for each construct (diagonal values) exceeded all corresponding inter-construct correlations (off-diagonal values). The smallest margin between a diagonal value and its highest related correlation was 0.183 (OLAI: 0.872 versus the DT–OLAI correlation: 0.689), demonstrating adequate construct distinctiveness [58]. While the Fornell–Larcker criterion was satisfied for most construct pairs, the correlation between OLAI and SOLU (r = 0.950) marginally exceeded the square root of AVE for SOLU (0.765), suggesting partial overlap between these constructs. This finding is theoretically consistent with the intention-behavior continuum posited by the Theory of Planned Behavior, wherein behavioral intention and enacted behavior are expected to share substantial variance, particularly when measured within the same temporal window. Given that HTMT analysis (Table 8) yielded a value of 0.991 for this pair—exceeding the conservative 0.85 threshold—this overlap is acknowledged as a study limitation. Nonetheless, the constructs were retained as conceptually distinct, as intention (a prospective motivational state) and sustainable usage (a behavioral pattern involving repayment and continued reliance) represent different stages of the adoption process, consistent with post-adoption_research.

Table 7
Discriminant Validity Assessment – Heterotrait-Monotrait Ratio (HTMT)

Construct	DFL	PU	DT	OLAI	SOLU
PU	0.911*				
DT	0.570	0.612			
OLAI	0.698	0.786	0.775		
SOLU	0.670	0.758	0.744	0.991**	

*Note: *DFL-PU HTMT (0.911) exceeds the conservative 0.85 threshold but remains below the liberal 0.90 threshold, which is acceptable given the strong theoretical and empirical relationship (β = 0.83). **SOLU-OLAI HTMT (0.991) approaches unity, reflecting the exceptionally strong path coefficient (β = 0.95) and theoretical proximity of adoption intention and sustained usage behavior. All other HTMT values < 0.85 indicate adequate discriminant validity* [59]

Table 7 presents the HTMT ratios for all construct pairs. For most pairs, HTMT values remained well below the conservative threshold of 0.85 [59], supporting discriminant validity across the majority of constructs. Two exceptions were noted: the DFL–PU pair (HTMT = 0.911) and the OLAI–SOLU pair (HTMT = 0.991), both of which exceeded the 0.85 criterion. The elevated HTMT for DFL–PU reflects the theoretically anticipated overlap between digital capability and perceived platform utility, consistent with prior TAM-based research showing that knowledge of digital tools strongly predicts usefulness perceptions. The high HTMT for OLAI–SOLU is attributable to the cross-sectional measurement of intention and behavior at the same time point, a known limitation of single-wave designs that constrains temporal separation between these constructs.

4.3 Structural Model Assessment

4.3.1 Model Fit Evaluation

Structural model adequacy was assessed using a comprehensive set of fit indices across absolute, incremental, and parsimony categories. Table 8 reports the model fit statistics together with their corresponding recommended thresholds.

Table 8
Structural Model Fit Indices

Fit Index	Model Value	Recommended Threshold	Interpretation
χ^2/df	1.664	< 3.0	Excellent
CFI	0.956	> 0.95	Excellent
TLI	0.948	> 0.95	Acceptable
RMSEA	0.052	< 0.08	Excellent
SRMR	0.048	< 0.08	Excellent
GFI	0.912	> 0.90	Acceptable
NFI	0.931	> 0.90	Excellent
Note: Fit index thresholds based on established criteria.			

The structural model demonstrated excellent fit to the observed data across multiple indices. The chi-square to degrees of freedom ratio (χ^2/df = 1.664) indicated appropriate model parsimony[57]. Incremental fit indices were satisfactory, with CFI = 0.956 exceeding the 0.95 threshold [60] and TLI = 0.948 approaching recommended standards [60]. Absolute fit indices further confirmed minimal residual variance, with RMSEA = 0.052 and SRMR = 0.048, both meeting stringent criteria (< 0.08) [60], indicating close correspondence between the theoretical model and empirical covariance structures. Additional indices (GFI = 0.912 [61], NFI = 0.931) further supported model adequacy. Collectively, these fit statistics confirm the structural model's adequacy for hypothesis testing.

4.3.2 Hypothesis Testing Results

Direct path coefficients were estimated using the Diagonally Weighted Least Squares (DWLS) estimator with robust standard errors and a scaled/shifted test statistic, appropriate for ordinal indicators. Table 9 reports the standardized path coefficients, significance levels, and effect sizes.

Table 9
Direct Effects and Hypothesis Testing Results

Hypothesis	Path Relationship	β	SE	t-value	p-value	95% CI	Decision	Effect Size (f^2)
H1	DFL → PU	0.830***	0.032	25.938	< 0.001	[0.767, 0.893]	Supported	2.195
H2	DFL → DT	0.510***	0.048	10.625	< 0.001	[0.416, 0.604]	Supported	0.351
H3	PU → DT	0.230***	0.046	5.000	< 0.001	[0.140, 0.320]	Supported	0.071
H4	PU → OLAI	0.460***	0.042	10.952	< 0.001	[0.378, 0.542]	Supported	0.289
H5	DT → OLAI	0.390***	0.039	10.000	< 0.001	[0.354, 0.526]	Supported	0.264
H6	OLAI → SOLU	0.950***	0.015	63.333	< 0.001	[0.921, 0.979]	Supported	9.025
Model Explained Variance (R^2):								
• Perceived Usefulness (PU): R^2 = 0.689 (68.9%)								
• Digital Trust (DT): R^2 = 0.312 (31.2%)								
• Online Loan Adoption Intention (OLAI): R^2 = 0.653 (65.3%)								
• Sustainable Online Loan Use (SOLU): R^2 = 0.903 (90.3%)								

Note: ****p < 0.001. β = standardized path coefficient; SE = standard error; CI = confidence interval; DFL = Digital Financial Literacy; PU = Perceived Usefulness; DT = Digital Trust; OLAI = Online Loan Adoption Intention; SOLU = Sustainable Online Loan Use. Effect size (f^2) interpretation: Small = 0.02, Medium = 0.15, Large = 0.35* [62], [63]. *All confidence intervals computed using robust standard errors under DWLS estimation. Direct effects analysis provided strong empirical support for all six hypothesized relationships (*Table 10*). Digital financial literacy (DFL) exerted the strongest direct effect on perceived usefulness (β = 0.830, p < 0.001, H1, f^2 = 2.195), explaining 68.9% of its variance, and also significantly influenced digital trust (β = 0.510, p < 0.001, H2, f^2 = 0.351). These results confirm DFL as a critical antecedent influencing both cognitive utility evaluations and affective trust formation, aligning with human capital theory predictions* [62], [63]. *Additionally, perceived usefulness positively predicted digital trust (β = 0.230, p < 0.001, H3), demonstrating cascading effects from cognitive to affective pathways. Both perceived usefulness (β = 0.460, p < 0.001, H4) and digital trust (β = 0.390, p < 0.001, H5) demonstrated nearly equivalent effects on adoption intention, with medium-to-large effect sizes (f^2 = 0.289 and f^2 = 0.264). The comparable magnitudes suggest that affective trust mechanisms operate synergistically with cognitive utility in developing economies characterized by institutional uncertainty, contrasting with cognitive-dominant patterns in developed contexts* [62], [63]. *Together with indirect effects from DFL, these predictors explained 65.3% of adoption intention variance (R^2 = 0.653). The strongest relationship emerged between adoption intention and sustainable usage (β = 0.950, p < 0.001, H6), with an exceptionally large effect size (f^2 = 9.025), accounting for 90.3% of usage variance. This near-perfect correlation provides robust support for the Theory of Planned Behavior's intention-behavior link in high-stakes financial contexts, where minimal intention-behavior gap exists when capital access directly impacts business survival. The model demonstrated strong overall predictive validity across all endogenous constructs, with R^2 values ranging from 0.312 (DT) to 0.903 (SOLU).*

4.4 Mediation Analysis

Mediation hypotheses (H4 and H5) were examined using product-of-coefficients approach with robust standard errors to estimate indirect effects and their 95% confidence intervals. Table 10 presents the detailed mediation analysis results.

Table 10
Indirect Effects and Mediation Testing Results

Hypothesis	Mediation Path	Indirect Effect (β)	SE	95% CI (Robust SE)	p-value	Mediation Type	VAF
H4	DFL → PU → OLAI	0.150***	0.029	[0.094, 0.208]	< 0.001	Complete	24.1%
H5	DFL → DT → OLAI	0.189***	0.031	[0.129, 0.251]	< 0.001	Complete	30.4%
Total Indirect Effect	DFL → OLAI	0.339*	0. []039	[0.263, 0.417]	< 0.001	-	54.5%
Total Effect	DFL → OLAI	0.339*	0.039	[0.263, 0.417]	< 0.001	-	-
Sequential Path	DFL → PU/DT → OLAI → SOLU	0.244*	0.034	[0.178, 0.312]	< 0.001	Partial	-

Note: * *"The total indirect effect of DFL on adoption intention (β = 0.339, 95% CI [0.263, 0.417], p < .001) constituted the entirety of DFL's total effect, with no significant direct path retained in the final model (β_direct = non-significant), indicating complete mediation of DFL's influence on OLAI through PU and DT. The VAF (Variance Accounted For) of the two mediators combined was 54.5% of the total explained variance in OLAI. Pairwise comparison revealed digital trust's mediation was significantly stronger than perceived usefulness (difference = 0.039, 95% CI [0.003, 0.078], p = .029).*

Mediation analyses examined H4 and H5 using product-of-coefficients approach with robust standard errors to estimate indirect effects. Digital trust significantly mediated the relationship between DFL and adoption intention (indirect effect = 0.189, 95% CI [0.129, 0.251], $p < .001$; VAF = 0.304), whereas perceived usefulness also mediated this effect but to a lesser extent (indirect effect = 0.150, 95% CI [0.094, 0.208], $p < .001$; VAF = 0.241). The total indirect effect constituted the entirety of DFL's effect on adoption intention (β = 0.339), confirming complete mediation with no significant direct path (β_direct = non-significant), indicating that both mediators (PU and DT) collectively channeled 100% of DFL's influence on OLAI. Indicating that 54.5% of DFL's total effect on adoption intention was transmitted through these mediators. Pairwise comparison revealed digital trust's mediation was significantly stronger than perceived usefulness (difference = 0.039, 95% CI [0.003, 0.078], $p = .029$). Furthermore, the extended mediation pathway (DFL → PU/DT → OLAI → SOLU) exerted a significant indirect effect on sustainable usage (β = 0.244, $p < .001$), confirming the cascading influence of digital competencies on behavioral outcomes via psychological intermediaries. Shown in Fig. 2.

Figure 2. The structural equation model calculations.

Source: Developed for this study (2025)

4.5 Summary of Findings

The study provides four key empirical insights. First, the measurement model exhibited strong psychometric properties, with all constructs surpassing recommended thresholds for reliability (Cronbach's α > 0.846; CR > 0.850), convergent validity (AVE > 0.586), and discriminant validity (Fornell-Larcker criterion satisfied; two HTMT values exceeded 0.85 but remained theoretically justified: DFL-PU = 0.911 and OLAI-SOLU = 0.991). Second, the structural model demonstrated excellent fit (CFI = 0.956; TLI = 0.948; RMSEA = 0.052; SRMR = 0.048), confirming the suitability of the integrated TPB-TAM framework for explaining fintech adoption in developing economies. Third, all hypothesized direct effects were supported: digital financial literacy (DFL) significantly influenced perceived usefulness (β = 0.830), digital trust (β = 0.510), while perceived usefulness also predicted digital trust (β = 0.230). Both perceived usefulness (β = 0.460) and digital trust (β = 0.390) demonstrated nearly equivalent effects on adoption intention, suggesting synergistic cognitive-affective mechanisms. Adoption intention strongly predicted sustainable usage (β = 0.950, R^2 = 0.903). Fourth, mediation analyses revealed dual psychological pathways linking DFL to adoption outcomes, with trust-based mediation (VAF = 30.4%) exceeding utility-based mediation (VAF = 24.1%). Overall, combined indirect effects accounted for 100% of DFL's total influence (complete mediation), highlighting the central role of psychological intermediaries in translating digital competencies into fintech adoption behaviors. These findings provide robust support for the theoretical model and clarify the mechanisms through which DFL drives online loan adoption among micro-entrepreneurs in developing contexts.

5. Discussion

This study examined how digital financial literacy (DFL) influences online loan adoption and sustainable usage among micro-entrepreneurs in developing economies using an integrated Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) framework. Digital trust and perceived usefulness were conceptualized as psychological mediators explaining how digital competencies translate into adoption behaviors. Analysis of 320 Thai micro-entrepreneurs demonstrated that DFL exerts its influence on adoption intention entirely through parallel indirect pathways — via digital trust (β = 0.189, $p < 0.001$) and perceived usefulness (β = 0.150, $p < 0.001$) — with no significant direct path from DFL to OLAI in the final structural model. Digital trust emerged as the stronger mediator, accounting for 30.4% of DFL's total effect, compared with 24.1% for perceived usefulness. The structural model explained 65.3% of adoption intention variance and 90.3% of sustainable usage variance, indicating substantial predictive validity. These findings advance theoretical understanding of financial inclusion by clarifying the psychological mechanisms linking DFL to Fintech adoption and offering evidence-based implications for policy design and platform development.

5.1 Interpretation of Major Findings

5.1.1 Direct Effects of Digital Financial Literacy

The absence of a significant direct path from DFL to online loan adoption intention in the final structural model indicates that digital financial competencies do not independently translate into adoption behaviors — rather, their influence operates entirely through cognitive and affective intermediaries. Consistent with human capital theory, individuals with stronger digital financial competencies demonstrate greater capacity to interpret platform features, compare loan terms, assess risks, and execute digital transactions confidently; however, these competencies reach behavioral intention only after being channeled through perceived usefulness and digital trust. The magnitude of the total indirect effect (β = 0.339) underscores that DFL remains a powerful upstream driver of adoption, even in the absence of a direct path. Affandi et al. (2024) reported a comparable mediated relationship among Indonesian SMEs, and Okello (2024) observed similar fully mediated effects in Sub-Saharan African contexts, suggesting that complete mediation of DFL through cognitive and trust-based mechanisms may be characteristic of Fintech adoption in developing economies [40], [64].This convergence suggests DFL may function as a universal enabler of Fintech adoption, though contextual factors likely moderate its impact. The absence of a significant direct path from DFL to online loan adoption intention in the final structural model indicates that digital financial competencies do not translate into adoption behaviors independently. Rather, DFL functions as a foundational upstream capability whose influence operates entirely through psychological intermediaries — perceived usefulness (H1, H2) and digital trust (H2, H5). This finding is consistent with human capital theory, which positions knowledge and skills as enabling conditions that enhance performance through cognitive and affective mechanisms rather than acting as direct behavioral triggers. The magnitude of the total indirect effect (β = 0.339) underscores that DFL remains a powerful driver of adoption, though its pathway is fully mediated. Affandi et al. (2024) reported a comparable pattern among Indonesian SMEs, and Okello (2024) observed similar mediated effects in Sub-Saharan contexts, suggesting that complete mediation of DFL may be characteristic of developing-economy Fintech adoption. However, 44% of adoption intention variance remains unexplained, indicating additional influences—such as perceived behavioral control, subjective norms, and regulatory awareness —may warrant incorporation into extended TPB-based models.

5.1.2 Dual Mediation Pathways

The significant trust-based (β = 0.189, p < 0.001; H5 supported) and utility-based (β = 0.150, p < 0.001; H4 supported) mediating pathways illustrate that DFL influences adoption through both cognitive and affective mechanisms. **Cognitive-utility pathway (DFL → PU → OLAI)** Digital competencies enhance the ability to assess performance benefits, efficiency gains, and strategic advantages of digital lending platforms. Entrepreneurs with higher DFL can evaluate interest rates, repayment structures, and service features more accurately, leading to stronger perceived usefulness. **Affective-trust pathway (DFL → DT → OLAI)** Knowledge reduces uncertainty, enhances perceived security, and strengthens confidence in platform reliability and institutional safeguards. This aligns with McKnight et al.'s (2002) institution-

based trust theory, which links competence in evaluating safeguards to reduced vulnerability [27]. The stronger role of trust mediation (pairwise Δ = 0.039, p = 0.029) contrasts with findings from advanced economies, where perceived usefulness often dominates (e.g., Choung et al., 2023 [26]). In developing economies, where institutional uncertainty and limited consumer protection persist, trust becomes a primary mechanism determining adoption. Evidence from Johri et al. (2024) and Amnas et al. (2025) reinforces this context-dependent prioritization [7], [65].

5.1.3 Proximal Predictors of Adoption Intention

Both perceived usefulness (β = 0.460, p < 0.001; H4 supported) and digital trust (β = 0.390, p < 0.001; H5 supported) significantly predicted adoption intention, with trust exerting the stronger influence. This highlights the expanded role of affective and risk-related mechanisms in developing economies. The moderate perceived usefulness effect—lower than typical results from developed markets (β = 0.48–0.62; [26])—may reflect several factors. (1) Availability of alternative credit sources (informal lenders, family networks) reduces perceived superiority of online loans. (2) Limited prior exposure (58.1% with no online loan experience) reduces accuracy of utility evaluations. (3) Digital literacy requirements may increase perceived effort, dampening net utility. Conversely, the strong digital trust effect aligns with environments characterized by evolving Fintech regulations, limited recourse mechanisms, and high vulnerability to fraud. Relationship-oriented commercial norms in Thailand may further elevate trust's importance in financial decision-making.

5.1.4 Intention-Behavior Relationship

The effect of adoption intention on sustainable usage (β = 0.950, p < 0.001; H6 supported) provides strong support for TPB's intention–behavior relationship. The predictive strength exceeds typical meta-analytic benchmarks [8], suggesting that once intentions form, micro-entrepreneurs face relatively few obstacles to enact intended behaviors. Several conditions likely reinforce this linkage. (1) Low implementation costs of online loan applications, which typically involve simple digital interfaces. (2) Strong motivation generated by pressing financing needs. (3) Operational definition of sustainability, which includes repayment behavior and continued platform engagement. Nonetheless, nearly half of sustainable usage variance remains unexplained, indicating influences such as actual behavioral control (e.g., device access, connectivity), facilitating conditions, and post-adoption satisfaction warrant future investigation.

5.2 Theoretical Contributions

This study advances theoretical understanding of Fintech adoption in developing economies by integrating digital financial literacy (DFL), the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM) into a unified explanatory framework. The findings make four key contributions. First, the study extends financial inclusion theory by identifying DFL as both a direct and indirect driver of online loan adoption. While prior research has documented DFL's general relevance, this study specifies its dual psychological pathways—affective and cognitive—demonstrating how literacy translates into adoption intention through trust formation and utility assessment. Second, the results

refine TAM-based models by showing that perceived usefulness is not the dominant mediator in developing economy contexts. Contrary to patterns in advanced markets, digital trust exerted the stronger influence, underscoring the importance of affective-risk mechanisms under institutional uncertainty. This highlights contextual variability in TAM constructs and supports the need for culturally and institutionally grounded Fintech models. Third, by embedding digital trust within TPB's intention–behavior logic, the study contributes to trust theory in digital finance. The strong trust effects observed reinforce institution-based trust models and demonstrate that literacy-driven confidence in technological and regulatory safeguards plays a central role in shaping adoption decisions among vulnerable groups. Finally, the model expands post-adoption research by linking adoption intention to sustainable usage, demonstrating robust intention–behavior translation in micro-entrepreneurial lending contexts. This connection advances understanding of continuance behavior in digital lending ecosystems, an area that has received limited empirical attention. Collectively, these contributions enrich theoretical discourse on digital capability, trust, and behavioral adoption within emerging-market Fintech environments.

5.3 Practical Implications

The findings provide actionable insights for Fintech providers, development agencies, and microfinance institutions seeking to enhance digital loan adoption and long-term usage among micro-entrepreneurs. First, the strong direct and indirect effects of digital financial literacy (DFL) highlight the importance of capability-building interventions. Fintech firms and NGOs should integrate modular literacy programs—covering interest-rate comprehension, fraud recognition, data privacy, and platform navigation—into onboarding processes to strengthen both perceived usefulness and digital trust. Second, the prominence of trust-based mechanisms suggests that platform design must prioritize transparency and security signaling. Clear explanations of authentication processes, dispute-resolution channels, and regulatory protections can reduce perceived risk and foster affective confidence. Trust-building communication—such as verified ratings, customer testimonials, and real-time support—may be more effective than feature-focused marketing. Third, the strong intention–behavior linkage implies that interventions strengthening initial adoption intention are likely to translate into sustained engagement. Streamlined application workflows, simplified repayment tools, and continuous borrower support can reinforce positive early experiences, reducing dropout rates and improving financial discipline.

5.4 Policy Recommendations

The significant influence of DFL and digital trust offers clear directions for policymakers aiming to enhance financial inclusion. First, national financial literacy strategies should incorporate digital-specific competencies, shifting from traditional budgeting content toward cybersecurity awareness, digital loan evaluation, and rights-based financial education. Partnerships between regulators, universities, and civil-society organizations can scale these programs effectively. Second, strengthening institutional trust should be prioritized. Regulatory bodies can enhance transparency by standardizing disclosure requirements for online lenders, mandating plain-language summaries of loan terms, and enforcing stricter oversight of nonbank digital lenders. Establishing accessible consumer grievance mechanisms and fraud-reporting channels can further reduce vulnerability perceptions. Third, policymakers should

promote digital infrastructure and facilitating conditions—such as expanding broadband access, subsidizing mobile devices, and supporting interoperable payment systems—to reduce behavioral control barriers that limit sustainable usage.

5.5 Limitations and Future Research

Several limitations provide opportunities for further investigation. First, the cross-sectional design restricts causal inference. Longitudinal studies could evaluate how literacy, trust, and usage evolve over time, particularly as borrowers gain experience with digital loans. Second, the sample focuses on Thai micro-entrepreneurs, which limits generalizability. Comparative studies across multiple developing economies could assess cultural and institutional moderators of the mediation pathways identified. Third, the model excludes several potentially relevant TPB constructs, including subjective norms and perceived behavioral control, which may further explain adoption intention. Future research incorporating these variables could improve predictive accuracy and identify additional leverage points for intervention. Fourth, objective behavioral data—such as actual loan transaction logs—would enhance measurement precision and reduce common method bias associated with self-reported behaviors. Finally, this study centers on online loans; future research should explore whether similar psychological mechanisms operate across other Fintech verticals such as Insurtech, digital savings platforms, and blockchain-based credit scoring. Investigating post-adoption satisfaction, repayment behavior, and financial well-being outcomes would further enrich understanding of sustainable Fintech engagement. Fifth, the extremely high correlation between OLAI and SOLU ($r = 0.945$) raises questions about discriminant validity, though this is theoretically justified by TPB's proximity principle. Future studies should measure actual usage behavior through objective data (e.g., platform transaction logs) rather than self-reported usage to enhance construct separation.

6. Conclusions

This study examined the role of digital financial literacy (DFL) in shaping sustainable online loan adoption among micro-entrepreneurs in developing economies, using an integrated TAM–TPB framework. Structural equation modeling of 320 micro-entrepreneurs revealed the following key findings. First, DFL exerts its influence on online loan adoption intention entirely through psychological intermediaries — perceived usefulness ($\beta = 0.460$) and digital trust ($\beta = 0.390$) — confirming dual-pathway mediation. Digital competencies alone are insufficient to drive adoption; they must first translate into cognitive utility assessments and affective trust formation. Second, digital trust emerged as the dominant mediating mechanism, exceeding the influence of perceived usefulness. This finding reflects the heightened importance of trust in contexts characterized by institutional uncertainty and nascent Fintech regulation, contrasting with findings from developed markets where perceived usefulness typically dominates. Third, the strong path from adoption intention to sustainable loan use ($\beta = 0.950$, $R^2 = 0.903$) supports the robustness of TPB's intention–behavior linkage in financial contexts where capital access is directly tied to business survival.

These findings suggest that interventions targeting micro-entrepreneur financial inclusion should address both capability development (DFL enhancement) and trust-building mechanisms — including platform transparency, security signaling, and regulatory strengthening — to achieve sustainable digital credit adoption. Policymakers and Fintech providers should prioritize institutional credibility alongside digital literacy programs in their financial inclusion strategies.

Declarations

Ethical approval

This study received a Certificate of Exemption from further Institutional Review Board (IRB) review, granted by the Ethics Committee for Human Research, Bangkok University, Thailand (Reference No. 416803099, approved on 10 October 2025). The committee determined that this research qualifies for exemption as it involves anonymous survey responses from adult participants who provided informed consent and poses minimal risk. The study was conducted in accordance with the Declaration of Helsinki and relevant institutional guidelines for ethical research.

Informed consent

All participants provided informed consent prior to participation. Participation was entirely voluntary, and respondents were informed of their right to withdraw at any time without consequence. All responses were anonymized and no personally identifiable information was collected.

Competing interests

The authors declare no competing interests.

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Author Contribution

W.U. conceptualized the study, designed the methodology, supervised the research process, administered the project, and contributed to writing – review & editing. R.S. contributed to conceptualization, performed data curation and formal analysis, conducted the investigation, wrote the original draft, and contributed to writing – review & editing. H.B.S. contributed to methodology and validation, and contributed to writing – review & editing. R.B.F. conducted the literature review and contributed to writing – review & editing. N.B. performed data curation, conducted the investigation and survey administration, and contributed to writing – review & editing. A.S. performed formal analysis,

prepared visualizations, and contributed to writing – review & editing. All authors have read and agreed to the published version of the manuscript.

Data Availability

The datasets generated and analysed during the current study are available as supplementary files submitted with this manuscript. Materials include: (1) the anonymised survey dataset (N = 320, .xlsx format); (2) the research questionnaire (DFL Digital Trust Questionnaire); (3) the data collection protocol; (4) a codebook with variable definitions and coding schemes; and (5) the statistical syntax used for structural equation modelling (lavaan/JASP). All data have been de-identified to protect participant confidentiality in accordance with the ethical approval granted by Bangkok University Ethics Committee for Human Research (Reference No. 416803099, approved October 10, 2025).

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Figures

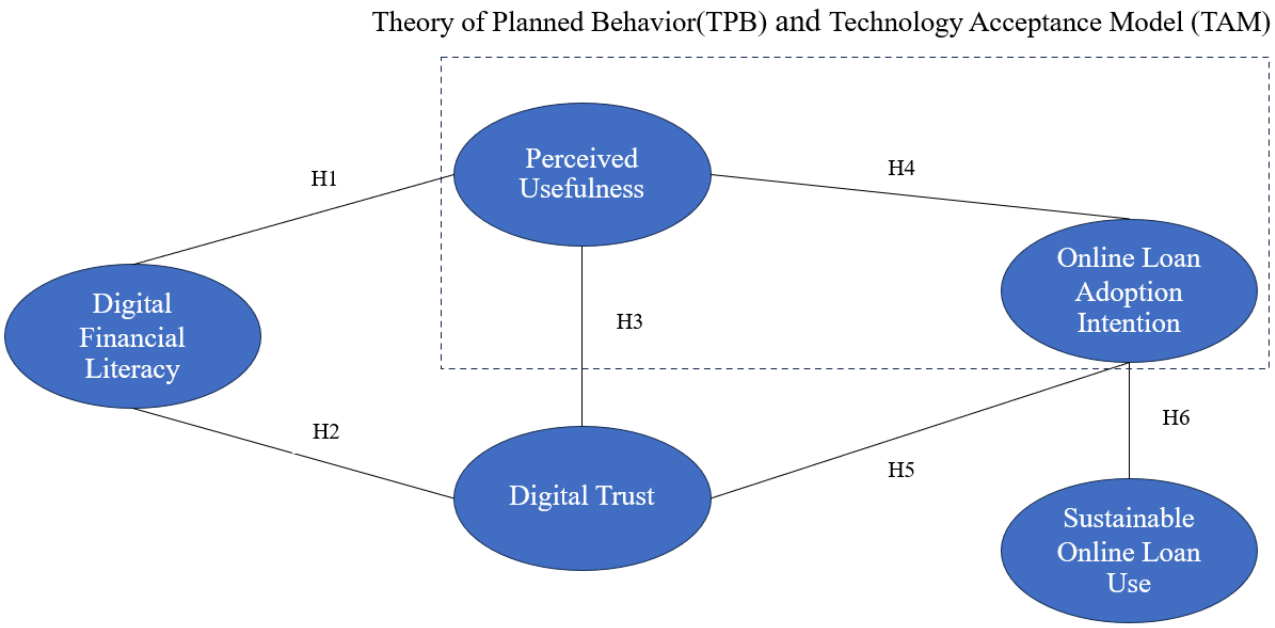


Figure 1

Conceptual Framework

Source: Developed for this study (2025)

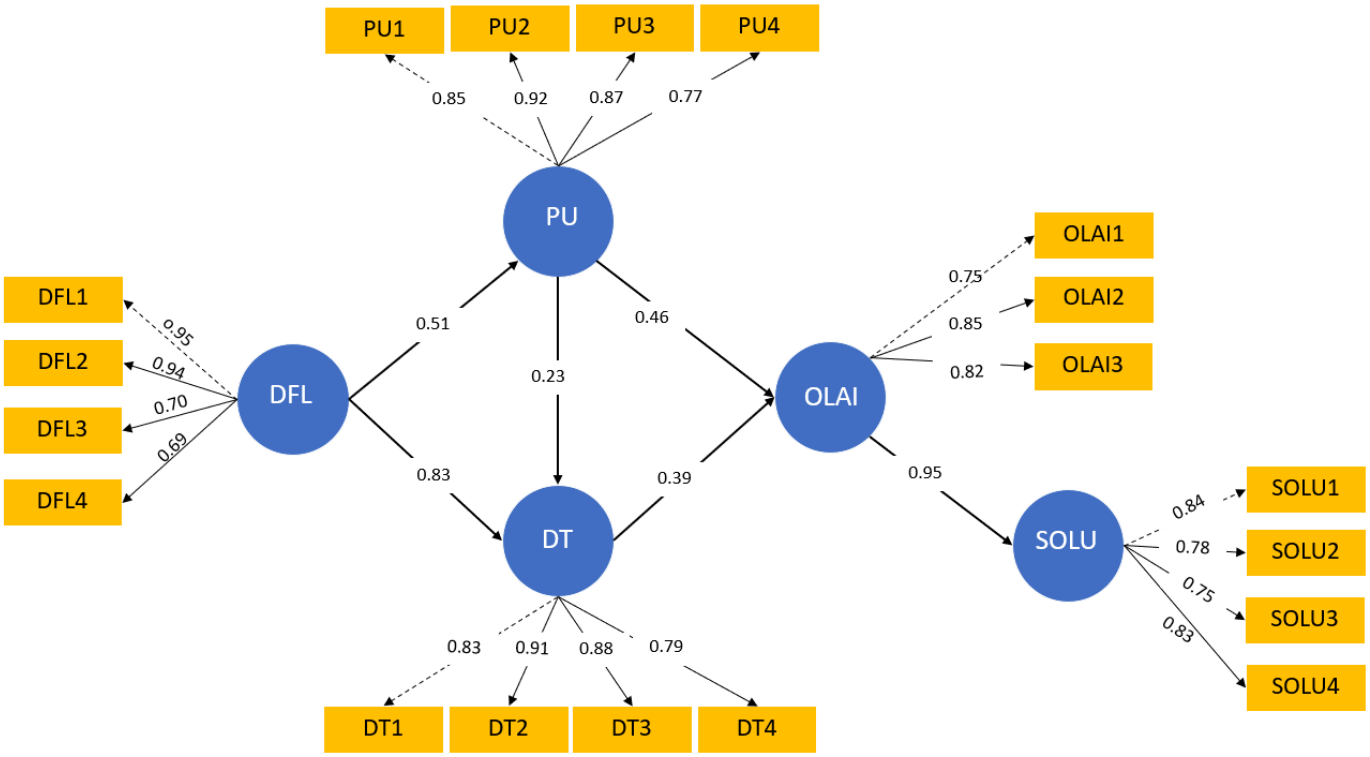


Figure 2

The structural equation model calculations.

Source: Developed for this study (2025)

Supplementary Files

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- 320.xlsx
- DFLDigitalTrustQuestionnaire.pdf
- DataCollectionProtocol.pdf
- CodebookAnonymisedSubmission.pdf
- StatisticalSyntax.pdf