DIGITAL LENDING STRATEGY IN AN EMERGING ECONOMY

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Abstract

As digital technologies continue to reshape the global financial landscape, digital lending has emerged as a rapidly growing alternative to traditional borrowing, particularly in developing economies (Sultan et al., 2023; Blend, 2022). This study investigates the key determinants influencing individuals' decisions to adopt digital lending in Thailand. Employing a quantitative research design, data were collected from 691 Thai respondents using convenience sampling. Binary logistic regression was applied to examine the relationships between demographic, financial, and perceptual variables and the likelihood of engaging in digital lending. The results indicate that specific personal financial conditions, such as being a student or having high monthly expenses, significantly decrease the likelihood of adopting digital lending. Conversely, having existing debt obligations and perceiving digital platforms as user-friendly are positively associated with interest in digital lending. Importantly, information awareness emerged as a critical factor in promoting informed financial decisions, highlighting the significance of financial literacy and transparent communication. This study contributes to a deeper understanding of digital lending behavior in emerging markets and offers practical insights for financial institutions and policymakers. It emphasizes the need for targeted financial education initiatives and user-centered platform design to encourage broader adoption and foster consumer trust in the digital financial ecosystem.

Keywords: Digital Lending, Adoption, Digital Financial Ecosystem

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1. INTRODUCTION

In the digital economy, as the world fully embraces the digital age, information and communication technologies (ICT) have become pivotal in transforming economic systems and human lifestyles, significantly altering consumer behaviors. Businesses must adapt swiftly to these changes to maintain their market share and meet the demands of modern consumers effectively (Kraus et al., 2021; Xia et al., 2023). Meanwhile, Thailand's digital economy has shown robust growth, with forecasts indicating that the gross merchandise volume (GMV) will rise from $31 billion in 2023 to $49 billion in 2026 — a 58.06% increase — and is expected to surge to $100–165 billion by 2030, maintaining its position as the second largest digital economy in the ASEAN region (Leesanguansuk, 2023; The Story Thailand, 2023).

Recently, smartphones have played a crucial role in various aspects of daily life, with rapid technological advancements increasing demand for mobile banking and mobile e-commerce services in Asia. Traditional financial transactions, once conducted through physical branches of financial institutions, have shifted to digital platforms due to technological advancements (Akhtar et al., 2019; Sultan et al., 2023). Digital lending, facilitated through digital platforms like mobile apps and websites, is reshaping financial services by providing faster, more accessible lending options. These services harness advanced technologies such as artificial intelligence (AI) and cloud computing to streamline the lending process, from the approval application, ensuring a seamless user experience. AI, for instance, is instrumental in automating credit assessments, thereby reducing manual processes and increasing the efficiency and accuracy of loan approvals. Moreover, the integration of end-to-end automation in the lending application process, powered by cloud technologies, enables the rapid deployment of new features and allows financial service providers to maintain a consistent experience across various devices and platforms. This digital transformation is part of a broader shift towards hyper-personalized financial services, where consumer preferences and behaviors are anticipated, and services are tailored to meet individual needs (Blend, 2022; Chitsingh & Jongadsayakul, 2022; Sawaengha et al., 2022).

Given the growing significance of digital financial services, the rising interest in digital lending highlights an urgent need for a deeper understanding of the factors that shape consumer adoption. A nuanced analysis of these determinants is essential for financial service providers seeking to enhance customer satisfaction, personalize offerings, and effectively serve diverse consumer segments. Identifying and addressing these factors is also critical for developing targeted marketing strategies that support the sustainable growth and competitiveness of digital lending platforms in an increasingly dynamic and digitalized financial landscape. Despite a growing body of literature on digital lending and financial technology adoption, most existing studies have centered primarily on technological dimensions, such as platform usability, system design, and technical infrastructure (Akhileshwari & Majumdar, 2023; Chen et al., 2023). While these aspects are undeniably important, limited research has examined the combined influence of demographic factors, financial behaviors, and consumer perceptions, particularly within the unique socio-economic context of emerging economies like Thailand. This study aims to bridge these gaps by employing a data-driven, exploratory approach to investigate the key variables influencing Thai consumers' intentions to adopt digital lending. Using binary logistic regression, the research integrates a wide range of demographic, financial, and perceptual factors to uncover statistically significant predictors of digital loan adoption. In doing so, this study contributes to a more comprehensive and locally relevant understanding of digital lending behavior. It offers valuable insights for practitioners, policymakers, and other stakeholders aiming to enhance financial inclusion, improve service delivery, and adapt digital lending models to the needs of emerging markets.

The paper is divided into six main sections. Section 1 introduces the topic. Section 2 includes a thorough literature review. Section 3 explains the research methodology. Section 4 presents the study's findings. Section 5 focuses on the findings. Section 6 covers the conclusions, limitations, and recommendations.

2. LITERATURE REVIEW

In the rapidly changing landscape of financial technology, digital banking has emerged as a critical enabler of financial inclusion, significantly altering the dynamics of access to financial services (Mittal et al., 2024; Nnaomah et al., 2024). Furthermore, the landscape of digital lending has undergone significant transformations, driven by advancements in technology and the proliferation of mobile applications. These digital platforms have revolutionized traditional lending mechanisms, offering consumers unprecedented convenience and accessibility. As more individuals turn to their smartphones for financial solutions, understanding the factors that influence their decisions to loan through applications becomes crucial (Akhileshwari & Majumdar, 2023; Chen et al., 2023; Uthaileang & Kiattisin, 2023). Consumer behavior involves both mental and physical activities that consumers perform when they search for, evaluate, purchase, and use products and services. Within the marketplace, consumers trade their limited resources, such as money, time, and effort, for items that hold value for them. For example, in studying how consumers purchase long-term care insurance, a researcher might examine several factors: the demographic characteristics of buyers (including income, age, and lifestyle), the timing of their purchases (whether triggered by personal events like a parent's illness or prompted by advertisements), their decision-making process (comparing various policies versus following recommendations), their motivations (such as the fear of depleting savings or the desire for quality care in old age), and their post-purchase satisfaction (including their satisfaction with the decision and the insurance provider). This comprehensive analysis provides valuable insights into consumer behavior, helping businesses tailor their strategies to meet consumer needs effectively (Cole, 2007).

Demographic factors play a vital role in understanding individual characteristics and are fundamental across various fields, including economics, marketing, and social sciences. These

variables, such as age, gender, income, expenses, education level, and geographic location, provide a foundational lens through which to analyze human behavior, preferences, and needs. For instance, age can influence lifestyle choices and financial priorities, while gender and gender identity may shape consumer preferences and risk perceptions. Income and expenditure levels reflect financial capacity and constraints, directly impacting consumption patterns and access to services such as digital lending. Educational attainment affects an individual's ability to comprehend and engage with complex financial products, and geographic location often determines access to infrastructure and technology. In business and marketing, demographic data are essential for market segmentation, enabling organizations to tailor products, services, and messaging to distinct consumer groups. While demographic attributes alone do not determine individual behavior, they offer valuable insights into group-level trends, such as purchasing habits or financial decision-making, facilitating more targeted and effective strategies for engagement and service delivery (Ansari et al., 2023; Cruz-Cárdenas et al., 2019; Kraiwanit et al., 2023).

According to Salas-Velasco (2022, 2024), financial education serves as a foundational tool for equipping individuals with the knowledge and skills necessary to navigate increasingly complex financial environments. As financial products and services become more diverse and accessible, the ability to make sound financial decisions is essential for personal and societal economic well-being. Comprehensive financial education promotes informed decision-making, fosters financial resilience, and reduces vulnerability to debt and financial mismanagement. In this context, Salas-Velasco (2022) emphasizes the pivotal role of financial education in strengthening financial literacy, which in turn significantly shapes individuals' financial decision-making, particularly in areas such as loan acquisition. The research demonstrates that targeted financial education programs positively influence students' financial knowledge and self-efficacy, thereby equipping them with the skills necessary to make more informed and responsible financial choices. Building on this, Salas-Velasco (2024) further explores how financial education can mitigate cognitive biases, specifically the availability heuristic, that often impair judgment in financial contexts. By encouraging the use of verified information and expert guidance over readily recalled or superficially persuasive cues, such interventions contribute to more rational and effective financial decision-making.

The innovation diffusion theory (IDT), developed by Rogers (2003), elucidates the process and factors contributing to the spread and acceptance of innovations within a society. The theory highlights four key components: innovation itself, communication channels, time, and social system members. It describes a five-stage decision-making process for adopting innovations: knowledge, persuasion, decision, implementation, and confirmation. Additionally, the theory identifies factors influencing innovation acceptance, such as the characteristics of the innovation, types of decision-making (voluntary, collective, or compulsory), communication channels, and attributes of social system members. It categorizes adopters into five groups: innovators, early adopters, early majority, late majority, and laggards. This framework is crucial for strategizing the promotion and diffusion of innovations across various sectors, including marketing, education, technology, and public policy.

Owusu et al. (2021) investigated the determinants influencing Ghanaian youth's intention to adopt mobile banking as a service delivery channel, utilizing the technology acceptance model (TAM) and the IDT as the theoretical frameworks. Their findings reveal that perceived ease of use, perceived usefulness, relative advantage, and complexity are significant predictors of mobile banking adoption intentions. Notably, the study demonstrates that complexity positively contributes to perceived ease of use, while relative advantage enhances perceived usefulness. These insights underscore the applicability of TAM and IDT in predicting technology adoption across varied contexts, offering valuable implications for understanding the motivational factors behind mobile banking adoption among young users in Ghana.

In a related study, Mensah and Khan (2024) explored the behavioral determinants of mobile banking service (MBS) acceptance in China, where mobile banking adoption remains relatively limited despite high smartphone penetration. By extending the unified theory of acceptance and use of technology (UTAUT) model, the researchers incorporated four key variables: performance expectancy, effort expectancy, perceived financial cost, and awareness. The study demonstrates that these factors significantly influence users' behavioral intention to adopt MBS. Additionally, technological infrastructure was found to enhance both performance expectancy and the intention to use MBS, while government support emerged as a critical factor shaping behavioral intentions. The findings underscore the importance of institutional and infrastructural support in promoting mobile banking adoption and offer valuable implications for both researchers and practitioners seeking to foster sustainable growth in the digital banking sector.

Self-service technology (SST) encompasses technological solutions that empower consumers to independently execute services or transactions without the need for direct interaction with service personnel. In the context of digital transformation, SST has gained prominence across numerous sectors, particularly within financial services. Common examples include ATMs and mobile banking applications, which facilitate user autonomy and convenience. Understanding the determinants of SST adoption is critical for organizations aiming to develop user-centric solutions that enhance customer satisfaction and maintain a competitive edge (Meuter et al., 2000; Natarajan et al., 2010). As financial institutions increasingly integrate digital technologies, the deployment of mobile banking applications as a form of SST has become widespread. The effectiveness of these applications depends heavily on the quality of service they deliver. In this regard, Leon et al. (2020) explore the influence of service quality dimensions, collectively conceptualized under the SSTQUAL model, on users' perceived value and satisfaction with MBSs. In their study, service quality is treated as a higher-order construct comprising seven first-order dimensions. The results indicate that high service quality significantly enhances both perceived value and customer satisfaction. These findings offer valuable implications for banks and technology developers, highlighting the importance of

delivering high-quality SST experiences to optimize user satisfaction and perceived value.

In this study, the relationship between three main categories of independent variables, demographic, behavioral, and perceptual, and the adoption of digital lending in Thailand is examined. Existing literature (Ansari et al., 2023; Katnic et al., 2024; Kraiwanit et al., 2023; Nasith, 2023; Normawati et al., 2021) suggests that these dimensions are critical in shaping consumer behavior toward financial technologies.

Demographic variables help contextualize how individual characteristics influence financial decisions, while behavioral factors capture patterns in financial management and loan-related actions. Perceptual variables, including attitudes and trust toward digital platforms, are particularly influential in adoption decisions. By integrating these three dimensions, this study seeks to provide a comprehensive perspective on the key determinants of digital lending adoption in an emerging market context.

Figure 1. Research model
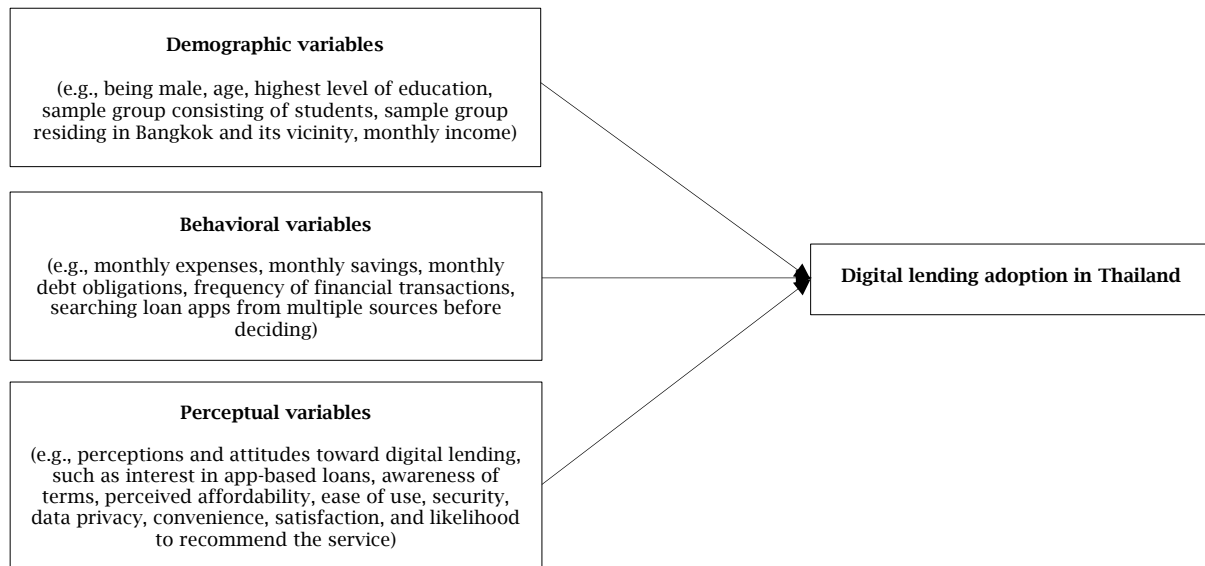
Source: Authors' elaboration.

As presented in Figure 1, the research model illustrates the relationship between three main categories of independent variables, demographic, behavioral, and perceptual, and the adoption of digital lending in Thailand. It proposes that individuals' decisions to engage with digital lending platforms are influenced by their personal characteristics, financial behaviors, and perceptions of digital financial services. This framework provides a structured approach to understanding the key factors that drive or hinder digital lending adoption in the context of an emerging economy.

3. METHODOLOGY

This study employed a quantitative methodology to identify the factors influencing individuals' intentions to adopt digital lending in Thailand, as it allows for systematic measurement and statistical analysis of relationships between variables. Specifically, binary logistic regression was applied, as the dependent variable, intention to adopt digital lending, is binary in nature (adopt vs. not adopt). This method is particularly suitable for estimating the likelihood of an outcome based on multiple independent variables, such as demographic, behavioral, and perceptual factors. It facilitates the identification of significant predictors and the strength of their influence, offering robust insights into the determinants of digital lending adoption.

Consistent with the principles of quantitative descriptive research, the primary aim was to describe prevailing trends and relationships

rather than to test specific causal hypotheses (Barroga & Matanguihan, 2022; Thomas & Zubkov, 2023). Reflecting its exploratory nature, the study adopted an inductive, data-driven approach, allowing patterns to emerge organically from the data. This approach is particularly appropriate when theoretical frameworks are limited and when multiple independent variables are under consideration. It also promotes analytical flexibility, reduces confirmation bias, and supports objective interpretation of empirical evidence, thereby enhancing understanding of consumer behavior in Thailand's digital lending market and informing future research and policy development.

3.1. Questionnaire design and instrument validation

In this quantitative study, the questionnaire was carefully designed and systematically implemented to ensure methodological rigor and align with the study's central aim, examining the determinants influencing consumer intention to adopt digital lending in an emerging economy. The instrument consisted of sections addressing demographic characteristics (such as gender, age, education, and income), financial behavior (including monthly expenses, savings, and debt obligations), and perceptions related to digital lending platforms (such as ease of use, perceived security, and awareness of loan terms and conditions). The questionnaire items were developed based on established literature, ensuring alignment with validated theoretical frameworks and empirical findings relevant to financial technology adoption.

To ensure contextual relevance, the items were adapted from Ansari et al. (2023), Cole (2007), Katnic et al. (2024), Kraiwanit et al. (2023), Nasith (2023), and Normawati et al. (2021), with modifications made to reflect the specific characteristics of Thai consumers in the digital lending environment. The adaptation process followed a structured approach, beginning with a content review to evaluate the relevance and clarity of original items in light of the study's objectives. Modifications were made to enhance cultural and contextual appropriateness while preserving the original constructs.

To ensure content validity, three academic experts reviewed the questionnaire for its suitability in measuring consumer perceptions and behaviors in Thailand's digital financial landscape. A pilot test with 30 participants then assessed clarity and identified ambiguous items. Following Aithal and Aithal (2020), this preliminary testing is essential before full deployment. Based on feedback, technical terms were simplified, response options expanded, question order adjusted for better flow, and redundant items removed. These revisions improved the questionnaire's validity and reliability.

3.2. Sample selection

The sample selection process was carefully designed to represent the target population, Thai residents aged 18 and older with experience or interest in digital lending. The minimum required sample size was calculated using Cochran's formula, based on a 95% confidence level and a 0.05 margin of error. Following guidelines from Uakarn et al. (2021), this yielded a minimum of 384 participants. To enhance the study's robustness and account for potential non-responses or incomplete data, the sample size was increased, resulting in 691 completed responses. Convenience sampling, a non-probability technique, was employed to efficiently access eligible participants who were readily available and met the inclusion criteria. This approach was appropriate given the study's digital focus and the need for timely data collection across a diverse demographic. Eligibility criteria included being at least 18 years old, residing in Thailand, and having experience with digital lending. This systematic sampling approach ensured data representativeness and reliability,

supporting a meaningful analysis of factors influencing digital lending adoption within Thailand's evolving financial landscape.

3.3. Data collection

Data collection was conducted via LINE, a popular digital platform in Thailand, chosen for its wide reach and accessibility. Its use enabled efficient participant engagement, real-time support, and high response quality. To facilitate ease of participation and maximize response rates, the survey was distributed from January to March 2024. This extended data collection window provided sufficient time to capture a wide range of consumer behaviors and attitudes, ensuring that the dataset reflected current trends and the evolving dynamics of digital lending in Thailand.

After data collection, the responses were screened for completeness and relevance, ensuring that the final dataset included only those who provided valid and consistent information related to digital lending. Furthermore, the research adhered to strict ethical standards: participants were provided with informed consent, which included details about the study's purpose, assurance of confidentiality, and a reminder of their voluntary participation rights, including the right to withdraw at any time. Eligibility was restricted to individuals aged 18 years and older. Only fully completed questionnaires were included in the analysis, ensuring the integrity and consistency of the dataset.

3.4. Data analysis

For the data analysis phase, both descriptive and inferential statistical techniques were applied using statistical software to explore the relationships among variables and identify key patterns related to digital lending. Descriptive statistics were used to summarize participant characteristics and responses, while inferential analysis provided insights into the predictors of individual intention to adopt digital lending. In this study, the dependent variable was individuals' intention to adopt digital lending in Thailand, and the independent variables are presented in Table 1.

Table 1. The study's independent variables

Variable	Explanation
MAL	Male
AGE	Age
EDU	Highest level of education
STD	Sample group consisting of students
BKK	Sample group residing in Bangkok and its vicinity
INC	Monthly income
EXP	Monthly expenses
SAV	Monthly savings
DEB	Monthly debt obligations
FRE	Frequency of financial transactions
LAA	Interest in loaning money through applications
INF	Awareness of information and terms of service for loaning through applications
SRH	Searching for loan apps from multiple sources before deciding to use one
RAB	Interest rates are not too high
RAN	The level of interest rates is appropriate
NEF	No charges or other fees are applied
USE	The application is easy to use and not complex
SAF	Confidence in the security of loaning money through the application
MIS	Risk of personal data being misused
CON	Loaning through the application makes transactions more convenient
SAT	Satisfaction with transactions conducted through the application
REC	Recommending others to try loaning money through the application

Source: Authors' elaboration.

Table 1 outlines the variables used in the study on digital lending, presenting each abbreviation along with its explanation. The focus is primarily on elements relevant to digital lending.

To examine the influence of multiple independent variables, including demographic, financial, and perceptual factors, on a binary dependent variable (the intention to adopt digital lending, coded as 1 = Yes and 0 = No), this study employed binary logistic regression analysis. As emphasized by Chatla and Shmueli (2017) and Taherdoost (2020), logistic regression is an appropriate and widely accepted statistical method for analyzing relationships where the outcome variable is dichotomous. This technique enables the estimation of the probability that an event will occur, in this case, a consumer's decision to engage in digital lending, based on the values of predictor variables.

By modeling the likelihood of binary outcomes, logistic regression facilitated a nuanced understanding of the factors that significantly influence consumer behavior in the context of digital financial services. The method not only allowed for the identification of statistically significant predictors but also provided interpretable measures of effect through odds ratios, illustrating the extent to which each variable increases or decreases the likelihood of adoption. This analytic strategy proved particularly valuable in uncovering critical insights relevant to digital lending adoption in Thailand's emerging economy.

4. RESULTS

A comprehensive dataset from 691 Thai participants was collected via online surveys. Each response was carefully coded and statistically analyzed, ensuring the findings aligned with research objectives and offered robust insights into the study's focus.

Table 2. Omnibus tests of model coefficients (all variables)

		χ^2	df.	Sig.
Step 1	Step	208.229	22	0.000
	Block	208.229	22	0.000
	Model	208.229	22	0.000

Source: Authors' elaboration.

Table 2 presents the Omnibus tests of model coefficients for a regression model used in the research. This table quantitatively assesses whether the set of predictors, as a whole, significantly impacts the response variable in the model. It provides a Chi-square (χ^2) statistic of 208.229, indicating a strong influence of the predictors on the outcome when considered together. The degrees of freedom (*df*) for the test are 22, and the significance level (*Sig.*) is reported as 0.000, underscoring that the model coefficients significantly differ from zero. This implies that the predictors collectively have a significant explanatory power regarding the dependent variable, thereby validating the relevance and contribution of these variables in the context of the study.

Table 3. Model summary (all variables)

	-2 log likelihood	Cox and Snell	Nagelkerke
Step 1	454.088[a]	0.260	0.422

Note: a. Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001.
Source: Authors' elaboration.

Table 3 provides critical statistics related to the fit and predictive accuracy of the regression model used in the research. The table reports a -2 log likelihood of 454.088, indicating the model's overall goodness-of-fit. Two types of R^2 values are provided: Cox and Snell and Nagelkerke, which measure the proportion of variance in the dependent variable that is predictable from the independent variables. The Cox and Snell R^2 value is 0.260, and the Nagelkerke R^2 value is 0.422, suggesting that a substantial portion of the variance in the response variable is explained by the model. The higher value of the Nagelkerke R^2 indicates a more accurate and reliable interpretation within the constraints imposed by the maximum value of the Cox and Snell R^2.

Table 4. Classification table (all variables)

			Predicted		
			Digital lending		Percentage correct
Step 1[a]	Observed		No	Yes	
	Digital lending	No	539	24	95.7
		Yes	79	49	38.3
	Overall percentage				85.1

Note: a. The cut value is 0.500.
Source: Authors' elaboration.

Table 4 assesses the predictive accuracy of the regression model employed in the research. It presents a detailed breakdown of the observed versus predicted categorization of responses regarding digital lending decisions ("No" and "Yes"). The table illustrates the model's ability to correctly classify cases into these two categories. For instance, out of the total "No" predictions, 539 cases were accurately predicted as "No" (true negatives), achieving a high correctness rate of 95.7%. Conversely, for "Yes" predictions, 49 out of 128 cases were correctly predicted (true positives), resulting in a lower correctness rate of 38.3%. The overall percentage correctness for the model, encompassing both categories, stands at 85.1%.

Table 5. Variables in the equation (all variables)

	Variable	B	S.E.	Wald	df.	Sig.	Exp(B)
Step 1[a]	MAL	0.268	0.253	1.121	1	0.290	1.308
	AGE	0.062	0.102	0.376	1	0.540	1.064
	EDU	-0.174	0.202	0.739	1	0.390	0.840
	STD	-1.302	0.320	16.571	1	0.000*	0.272
	BKK	-0.196	0.256	0.587	1	0.444	0.822
	INC	0.132	0.173	0.581	1	0.446	1.141
	EXP	-0.535	0.160	11.165	1	0.001*	0.586
	SAV	0.052	0.157	0.110	1	0.740	1.053
	DEB	0.397	0.146	7.430	1	0.006*	1.487
	FRE	-0.273	0.109	6.282	1	0.112	0.761
	LAA	1.144	0.214	28.567	1	0.000*	3.138
	INF	0.519	0.184	7.945	1	0.005*	1.680
	SRH	0.085	0.172	0.244	1	0.622	1.088
	RAB	-0.236	0.209	1.269	1	0.260	0.790
	RAN	-0.197	0.231	0.727	1	0.394	0.821
	NEF	-0.052	0.214	0.058	1	0.809	0.950
	USE	0.041	0.198	0.043	1	0.835	1.042
	SAF	0.341	0.187	3.323	1	0.068	1.406
	MIS	-0.152	0.179	0.718	1	0.397	0.859
	CON	-0.004	0.202	0.000	1	0.986	0.996
	SAT	-0.164	0.282	0.339	1	0.560	0.849
	REC	0.029	0.248	0.014	1	0.906	1.030
	Constant	-3.853	0.833	21.396	1	0.000	0.021

Note: a. Variable(s) entered on step 1: MAL, AGE, EDU, STD, BKK, INC, EXP, SAV, DEB, FRE, LAA, INF, SRH, RAB, RAN, NEF, USE, SAF, MIS, CON, SAT, and REC. * p < 0.05.
Source: Authors' elaboration.

Table 5 provides detailed statistical outputs from the logistic regression model, showcasing the relationship between each predictor variable and the likelihood of adopting digital lending. The results of the binary logistic regression analysis revealed five statistically significant variables influencing the likelihood of adopting digital lending. Student status (*STD*) exhibited a significant negative relationship (B = -1.302, Exp(B) = 0.272), indicating that students are considerably less likely to express interest in digital lending. Similarly, monthly expenses (*EXP*) had a negative effect (B = -0.535, Exp(B) = 0.586), suggesting that individuals with higher monthly expenditures are less inclined to engage in digital lending. In contrast, monthly debt (*DEB*) was positively associated with adoption (B = 0.397, Exp(B) = 1.487), implying that those with existing debt obligations are more likely to consider digital lending as a financial solution. The variable interest in loaning through apps (*LAA*) demonstrated a strong positive effect (B = 1.144, Exp(B) = 3.138), highlighting the significance of technological preferences in influencing borrowing behavior. Lastly, information awareness (*INF*) also showed a positive relationship (B = 0.519, Exp(B) = 1.680), underscoring the role of *inf*ormed decision-making in driving the adoption of digital lending. These findings suggest that both financial conditions and perceptual factors play a critical role in shaping consumer engagement with digital financial services in Thailand.

By including only the five statistically significant independent variables with p-values below 0.05, *STD*, *EXP, DEB, LAA,* and awareness of loan terms (*INF*), the logistic regression model hones in on their individual and combined effects on the likelihood of engaging in digital lending. This focused approach refines the analysis, highlighting the primary factors that influence consumer decisions regarding digital lending. Consequently,

the model offers clearer insights into consumer behavior and improves the accuracy of predicting key drivers behind digital lending decisions.

Table 6. Omnibus tests of model coefficients (only significant variables)

Step 1	χ^2	df.	Sig.
Step	188.262	5	0.000
Block	188.262	5	0.000
Model	188.262	5	0.000

Source: Authors' elaboration.

Table 6 assesses the significance of the predictors in the model, showing a Chi-square value of 188.262 with 5 degrees of freedom. The highly significant p-value of 0.000 indicates that the predictors collectively have a strong influence on the outcome variable. This confirms the model's effectiveness in explaining and predicting variations in the dependent variable.

Table 7. Model summary (only significant variables)

Step 1	-2 Log likelihood	Cox and Snell	Nagelkerke
	474.054[a]	0.238	0.387

Note: a. Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001.
Source: Authors' elaboration.

Table 7 presents key fit statistics for the regression model, including the -2 log likelihood, Cox and Snell's R^2, and Nagelkerke's R^2. The -2 log likelihood value of 474.054 indicates the overall model fit, while the Cox and Snell R^2 of 0.238 and Nagelkerke R^2 of 0.387 reflect the proportion of variance explained by the model. These values suggest moderate explanatory power, with Nagelkerke's R^2 offering a more optimistic measure of predictive accuracy.

Table 8. Classification table (only significant variables)

	Observed		Predicted		
			Digital lending		Percentage correct
			No	Yes	
Step 1[a]	Digital lending	No	536	27	95.2
		Yes	83	45	35.2
	Overall percentage				84.1

Note: a. The cut value is 0.500.

Table 8 assesses the regression model's predictive accuracy by comparing observed and predicted outcomes. It shows high accuracy for predicting "No" responses at 95.2% (536 of 563 cases correctly classified), but lower accuracy for "Yes" responses at 35.2% (45 of 128 cases correctly classified). Overall, the model achieves an accuracy rate of 84.1%, indicating strong performance in identifying negative cases, though with room for improvement in predicting positive responses.

Table 9. Variables in the equation (only significant variables)

	Variable	B	S.E.	Wald	df.	Sig.	Exp(B)
Step 1[a]	STD	-1.336	0.274	23.734	1	0.000[*]	0.263
	EXP	-0.470	0.122	14.923	1	0.000[*]	0.625
	DEB	0.421	0.132	10.195	1	0.001[*]	1.524
	LAA	0.928	0.154	36.468	1	0.000[*]	2.528
	INF	0.620	0.157	15.630	1	0.000[*]	1.860
	Constant	-5.098	0.597	72.867	1	0.000[*]	0.006

Note: a. Variable(s) entered on step 1: STD, EXP, DEB, LAA, and INF. * $p < 0.05$.
Source: Authors' elaboration.

Table 9 presents a refined version of the prior logistic regression model, focusing on the statistically significant variables influencing interest in digital lending. This streamlined model includes five variables with p-values below 0.05, offering a more targeted analysis of the key factors shaping digital lending adoption. *STD* is the strongest negative predictor in the model, with a B coefficient of -1.336 and Exp(B) of 0.263. This indicates that being a student significantly decreases the likelihood of interest in digital lending by a factor of about 0.737 (1 - 0.263 = 0.737). Similarly, *EXP*, with a B coefficient of -0.470 and Exp(B) of 0.625, shows that higher *EXP* reduce the likelihood of interest in digital lending. For each unit increase in expenses, the odds of adopting digital lending decrease by a factor of about 0.375 (1 - 0.625 = 0.375). In contrast, *DEB*, with a positive B coefficient of 0.421 and Exp(B) of 1.524, increases the likelihood of interest in digital lending. For each unit increase in debt, the odds of engaging with digital lending increase by a factor of about 1.524. *LAA* emerges as the strongest positive predictor, with a B coefficient of 0.928 and Exp(B) of 2.528. This suggests that interest in app-based loans increases the odds of adopting digital lending by a factor of about 2.528. Lastly, *INF,* with a B coefficient of 0.620 and Exp(B) of 1.860, demonstrates that greater awareness of digital financial services increases the likelihood of interest in digital lending by a factor of about 1.860. All these variables are highly statistically significant, with p-values of 0.000 or 0.001, offering robust evidence of their influence on digital lending interest. This model enhances clarity by excluding non-significant predictors, thereby deepening the understanding of key drivers and barriers to digital lending adoption in the Thai context.

5. DISCUSSION

This study investigated the key determinants influencing individuals' decisions to adopt digital lending in Thailand, revealing that *STD, EXP, DEB,* interest in app-based loans, and awareness of information are significant factors.

The finding reveals that students are significantly less inclined to utilize digital lending services, primarily due to limited financial resources and a lack of established credit history, both of which are critical criteria in digital lending assessments. The study's findings align with Elliott and Lewis (2015), Reid (2024), and Widener (2017), who note that students often experience financial instability and lower income levels, making it more difficult to secure loans. This economic vulnerability is further compounded by a reluctance to incur debt during key transitional life stages, driven by concerns over long-term financial consequences.

EXP emerge as a significant deterrent to digital lending adoption, as higher financial outlays reduce the capacity for additional financial commitments. Individuals with higher monthly expenditures may prioritize maintaining financial stability over incurring new obligations, thereby decreasing their likelihood of seeking loans. Furthermore, the financial stress associated with substantial *EXP* can reinforce cautious financial behavior, particularly among lower-income groups. These insights underscore the critical role of *EXP* in shaping individual financial decision-making and attitudes toward adopting digital lending services. This finding aligns with Chavali et al. (2021), Jumady et al. (2024), and Rahman et al. (2021), who emphasize that financial behaviors related to managing expenses, savings, and credit strongly influence financial well-being and decisions regarding new debt acquisition.

Conversely, individuals burdened with existing debts appear more predisposed to explore digital lending solutions. This trend likely reflects a strategic approach to debt management, where online loans might offer more favorable terms or the possibility of consolidating existing debts under more manageable conditions. As stated by Dow and Voigt (2025), Kaminskyi et al. (2024), and Veling (2025), online lenders are distinguished by their streamlined application processes and rapid funding capabilities, advantages that make them particularly

appealing for individuals seeking debt consolidation solutions when compared to traditional banking institutions.

Remarkably, an interest in app-based loan services strongly encourages digital lending engagement. This enthusiasm can be linked to the perceived ease of use, immediacy, and user-friendly interfaces provided by modern financial apps, which align well with the lifestyle and preferences of tech-savvy consumers. In accordance with the findings presented by Guo et al. (2023), Naruetharadhol et al. (2021), and Tarawneh et al. (2023), ease of use emerges as a crucial determinant in the adoption of MBSs. The study underscores the significance of user-friendly interfaces and streamlined processes in facilitating the utilization of digital banking platforms among consumers in the regions.

Additionally, *INF* plays a pivotal role in shaping individuals' decisions to adopt digital lending. A well-informed user base tends to be more confident in navigating the intricacies of online loans, driven by a clear understanding of the terms, benefits, and potential pitfalls of such financial instruments. The presence of accurate and accessible information not only demystifies the process but also empowers consumers to make decisions that align with their financial goals and circumstances. In line with Khan (2024), Solarz and Adamek (2023), and Wang et al. (2015), the movement towards online lending is supported by the overall trust and perception of information integrity on digital platforms, which lowers perceived information asymmetry between borrowers and lenders. When potential borrowers perceive that information asymmetry is low, their trust in the platform increases, positively impacting their intention to use online lending services

This analysis underscores the complexity of consumer behavior in the digital lending market, suggesting that financial service providers need to consider a broad spectrum of psychological, economic, and informational factors when designing and marketing their products. Understanding these dynamics is crucial for tailoring offerings that not only meet the diverse needs of potential borrowers but also enhance their overall experience and satisfaction with digital financial services.

6. CONCLUSION

This study illuminates the multifaceted factors influencing individuals' decisions to engage with digital lending in Thailand. The findings reveal that personal financial circumstances such as being a student or having high monthly expenses significantly deter interest in digital lending services, while existing debts and the appeal of user-friendly app-based lending platforms encourage it. Moreover, the critical role of *INF* in facilitating informed decision-making highlights the necessity for clear and accessible financial education. These insights

suggest that for digital lending platforms to effectively attract and serve a diverse clientele, they must consider these varying consumer needs and preferences. Tailoring loan products and enhancing user experiences, particularly through educational resources that bridge knowledge gaps, could lead to broader adoption and more satisfied customers in the digital lending space. This approach not only aligns with consumer behaviors and preferences but also fosters a more informed and financially literate user base, ultimately contributing to the stability and growth of the fintech industry. In summary, the study highlights the necessity for digital lending platforms to adapt to the heterogeneous needs of their users through tailored products and comprehensive financial education. By doing so, these platforms can enhance user satisfaction and adoption rates, fostering a more inclusive and robust digital financial ecosystem and beyond.

This study offers important practical, policy, and academic contributions. Practically, it emphasizes the need for improved financial education to enhance consumer literacy and informed decision-making in digital lending. It also underscores the importance of user-friendly platforms and targeted support for vulnerable groups, such as students and those with high expenses. Policymakers can draw on these findings to design regulatory frameworks that promote transparency, consumer protection, and financial inclusion. Academically, the study advances knowledge on digital financial service adoption by integrating financial literacy and TAM. It provides empirical evidence from Thailand, highlighting the roles of service quality, user experience, and *INF*. These insights offer a foundation for future research on the long-term impacts of financial education and platform design in the evolving digital finance landscape.

Despite the valuable insights offered by this study, several limitations should be acknowledged. First, the use of convenience sampling may restrict the generalizability of the findings to the wider Thai population. Future research should consider employing random sampling techniques to achieve a more representative sample. Second, the reliance on self-reported data introduces potential biases, such as social desirability and recall bias. Incorporating objective behavioral data or adopting mixed-method approaches could help validate and enrich the findings. Lastly, while the study examines key determinants of digital lending adoption, it does not account for all relevant variables. Future studies should explore additional factors, such as trust in digital financial services and the impact of technological innovation. Addressing these limitations would enhance the robustness and applicability of future research, supporting the development of more effective strategies to promote consumer participation in the digital financial ecosystem.

REFERENCES

Aithal, A., & Aithal, P. S. (2020). Development and validation of survey questionnaire & experimental data — A systematical review-based statistical approach. *International Journal of Management, Technology, and Social Sciences, 5*(2), 233–251. http://doi.org/10.5281/zenodo.4179499

Akhileshwari, A., & Majumdar, J. (2023). Factors influencing the adoption of digital lending: A comprehensive literature review. *Tuijin Jishu/Journal of Propulsion Technology, 44*(6), 98–111. https://www.propulsiontechjournal.com/index.php/journal/article/view/3061

Akhtar, S., Irfan, M., Sarwar, A., Asma, & Rashid, Q. U. A. (2019). Factors influencing individuals' intention to adopt mobile banking in China and Pakistan: The moderating role of cultural values. *Journal of Public Affairs, 19*(1), Article e1884. https://doi.org/10.1002/pa.1884

Ansari, Y., Albarrak, M. S., Sherfudeen, N., & Aman, A. (2023). Examining the relationship between financial literacy and demographic factors and the overconfidence of Saudi investors. *Finance Research Letters, 52,* Article 103582. https://doi.org/10.1016/j.frl.2022.103582

Barroga, E., & Matanguihan, G. J. (2022). A practical guide to writing quantitative and qualitative research questions and hypotheses in scholarly articles. *Journal of Korean Medical Science, 37*(16), Article e121. https://doi.org/10.3346/jkms.2022.37.e121

Blend. (2022, July 15). *The latest digital lending trends impacting financial services.* https://blend.com/blog/thought-leadership/digital-lending-trends/

Chatla, S. B., & Shmueli, G. (2017). An extensive examination of regression models with a binary outcome variable. *Journal of the Association for Information Systems, 18*(4), 340–371. https://doi.org/10.17705/1jais.00455

Chavali, K., Mohan Raj, P., & Ahmed, R. (2021). Does financial behavior influence financial well-being? *The Journal of Asian Finance, Economics and Business, 8*(2), 273–280. https://doi.org/10.13106/jafeb.2021.vol8.no2.0273

Chen, R., Wang, S., Zhu, Z., Yu, J., & Dang, C. (2023). Credit ratings of Chinese online loan platforms based on factor scores and K-means clustering algorithm. *Journal of Management Science and Engineering, 8*(3), 287–304. https://doi.org/10.1016/j.jmse.2022.12.003

Chitsingh, A., & Jongadsayakul, W. (2022). The study of borrowing behaviour in mobile banking application in Thailand. *Journal of Modern Learning Development, 7*(9), 296–311. https://so06.tci-thaijo.org/index.php/jomld/article/view/257232

Cole, C. A. (2007). Consumer behavior. In J. E. Birren (Ed.), *Encyclopedia of gerontology* (2nd ed., pp. 307–315). Elsevier. https://doi.org/10.1016/B0-12-370870-2/00040-8

Cruz-Cárdenas, J., Zabelina, E., Deyneka, O., Guadalupe-Lanas, J., & Velín-Fárez, M. (2019). Role of demographic factors, attitudes toward technology, and cultural values in the prediction of technology-based consumer behaviors: A study in developing and emerging countries. *Technological Forecasting and Social Change, 149,* Article 119768. https://doi.org/10.1016/j.techfore.2019.119768

Dow, N., & Voigt, K. (2025, June 5). *Should you apply for a loan online vs in person? How to choose.* NerdWallet. https://www.nerdwallet.com/article/loans/personal-loans/online-loan-or-bank-loan

Elliott, W., & Lewis, M. (2015). Student debt effects on financial well-being: Research and policy implications. *Journal of Economic Surveys, 29*(4), 614–636. https://doi.org/10.1111/joes.12124

Guo, H., Ling, Q., Nan, X., Wei, Y.-C., & Wunsuk, P. (2023). Technology acceptance model to intention of use the mobile banking services in Chiang Mai Province, Thailand. *International Journal of Sociologies and Anthropologies Science Reviews, 3*(4), 131–140. https://doi.org/10.60027/ijsasr.2023.3077

Jumady, E., Alam, S., Hasbiyadi, H., Fajriah, Y., & Anggraini, Y. (2024). The effect of financial planning on consumer debt management: the role of financial literacy, self-efficacy, and financial motivation. *Atestasi: Jurnal Ilmiah Akuntansi, 7*(1), 340–368. https://doi.org/10.57178/atestasi.v7i1.793

Kaminskyi, A., Pysanets, K., & Petrovskyi, O. (2024). Biznes-protsesy spozhyvchoho kredytuvannya bankivs'kykh ta nebankivs'kykh finansovykh ustanov: Osnovni vidminnosti [Consumer lending business processes for banking and non-banking financial institutions: Core differences]. *Herald of Khmelnytskyi National University. Economic Sciences, 336*(6), 587–592. https://doi.org/10.31891/2307-5740-2024-336-88

Katnic, I., Katnic, M., Orlandic, M., Radunovic, M., & Mugosa, I. (2024). Understanding the role of financial literacy in enhancing economic stability and resilience in Montenegro: A data-driven approach. *Sustainability, 16*(24), Article 11065. https://doi.org/10.3390/su162411065

Khan, M. T. I. (2024). Trust in peer-to-peer (P2P) lending platforms in Malaysia: Understanding the determinants from retail investors' perspectives. *Journal of Economic and Administrative Sciences, 40*(5), 936–955. https://doi.org/10.1108/JEAS-08-2021-0148

Kraiwanit, T., Limna, P., Wattanasin, P., Asanprakit, S., & Thetlek, R. (2023). Adoption of Worldcoin digital wallet in Thailand. *Research in Globalization,* Article 100179. https://doi.org/10.1016/j.resglo.2023.100179

Kraus, S., Jones, P., Kailer, N., Weinmann, A., Chaparro-Banegas, N., & Roig-Tierno, N. (2021). Digital transformation: An overview of the current state of the art of research. *Sage Open, 11*(3). https://doi.org/10.1177/21582440211047576

Leesa-nguansuk, S. (2023, November 3). Thailand set to remain No.2 digital economy. *Bangkok Post.* https://www.bangkokpost.com/business/general/2677164/

Leon, M. V. D., Atienza, R. P., & Susilo, D. (2020). Influence of self-service technology (SST) service quality dimensions as a second-order factor on perceived value and customer satisfaction in a mobile banking application. *Cogent Business & Management, 7*(1), Article 1794241. https://doi.org/10.1080/23311975.2020.1794241

Mensah, I. K., & Khan, M. K. (2024). Unified theory of acceptance and use of technology (UTAUT) model: Factors influencing mobile banking services' adoption in China. *SAGE Open, 14*(1). https://doi.org/10.1177/21582440241234230

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., & Bitner, M. J. (2000). Self-service technologies: Understanding customer satisfaction with technology-based service encounters. *Journal of Marketing, 64*(3), 50–64. https://doi.org/10.1509/jmkg.64.3.50.18024

Mittal, S., Tayal, A., Singhal, S., & Gupta, M. (2024). Fintech's transformative influence on traditional banking strategies and its role in enhancing financial inclusion. *Journal of Informatics Education and Research, 4*(2), 345–352. https://doi.org/10.52783/jier.v4i2.774

Naruetharadhol, P., Ketkaew, C., Hongkanchanapong, N., Thaniswannasri, P., Uengkusolmongkol, T., Prasomthong, S., & Gebsombut, N. (2021). Factors affecting sustainable intention to use mobile banking services. *SAGE Open, 11*(3), 1–13. https://doi.org/10.1177/21582440211029925

Nasith, A. (2023). Perception of ease, risk, and benefits in online loans: A study in lower middle communities. *Indonesian Interdisciplinary Journal of Sharia Economics, 6*(3), 3481–3498. https://www.e-journal.uac.ac.id/index.php/iijse/article/view/5193

Natarajan, T., Balasubramanian, S. A., & Manickavasagam, S. (2010). Customer's choice amongst self service technology (SST) channels in retail banking: A study using analytical hierarchy process (AHP). *Journal of Internet Banking and Commerce, 15*(2), 1–16. https://www.researchgate.net/publication/286749345

Nnaomah, U. I., Aderemi, S., Olutimehin, D. O., Orieno, O. H., & Ogundipe, D. O. (2024). Digital banking and financial inclusion: A review of practices in the USA and Nigeria. *Finance & Accounting Research Journal, 6*(3), 463–490. https://doi.org/10.51594/farj.v6i3.971

Normawati, R. A., Rahayu, S. M., & Worokinasih, S. (2021). Financial knowledge, digital financial knowledge, financial attitude, financial behaviour and financial satisfaction on millennials. In M. Rachmawati, F. J. Nugroho, E. E. Supriyanto, H. Saksono, A. N. Cahyo, F. Natalia, S. Silviana, & E. Windy (Eds.), *Proceedings of the 1st International Conference on Law, Social Science, Economics, and Education* (pp. 317–328). https://doi.org/10.4108/eai.6-3-2021.2305967

Owusu, G. M. Y., Bekoe, R. A., Addo-Yobo, A. A., & Otieku, J. (2021). Mobile banking adoption among the Ghanaian youth. *Journal of African Business, 22*(3), 339–360. https://doi.org/10.1080/15228916.2020.1753003

Rahman, M., Isa, C. R., Masud, M. M., Sarker, M., & Chowdhury, N. T. (2021). The role of financial behaviour, financial literacy, and financial stress in explaining the financial well-being of B40 group in Malaysia. *Future Business Journal, 7,* Article 52. https://doi.org/10.1186/s43093-021-00099-0

Reid, C. A. (2024). *Loan debt burden, student experiences, and livelihood: A study examining relationships between students' education costs, financial viability, and life impact* [Doctoral dissertation, Eastern Michigan University]. Eastern Michigan University. https://commons.emich.edu/theses/1227/

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Salas-Velasco, M. (2022). Causal effects of financial education intervention aimed at university students on financial knowledge and financial self-efficacy. *Journal of Risk and Financial Management, 15*(7), Article 284. https://doi.org/10.3390/jrfm15070284

Salas-Velasco, M. (2024). Debiasing the availability heuristic in student loan decision-making. *Empirica, 51*(2), 501–528. https://doi.org/10.1007/s10663-024-09609-z

Sawaengha, P., Thammajariyawat, M., & Leemakdej, A. (2022). The business service model of digital personal loans in Thailand. *Asian Administration & Management Review, 5*(1), 65–71. https://doi.nrct.go.th/admin/doc/doc_619084.pdf

Solarz, M., & Adamek, J. (2023). Trust and personal innovativeness as the prerequisites for using digital lending services offered by FinTech lenders. *Annales Universitatis Mariae Curie-Skłodowska, Sectio H–Oeconomia, 57*(1), 197–218. https://journals.umcs.pl/h/article/view/14994

Sultan, M. F., Tunio, M. N., Shamsi, A. F., & Imamuddin. (2023). Mobile banking in the context of developing Asian countries: A thorough perspective based on customer's intention, benefits, challenges, and security issues. In C.-M. Leong, M. Ali, S. A. Raza, C.-H. Puah, & I. H. Eksi (Eds.), *Financial inclusion across Asia: Bringing opportunities for businesses* (pp. 87–96). Emerald Publishing Limited. https://doi.org/10.1108/978-1-83753-304-620231007

Taherdoost, H. (2020). Different types of data analysis; Data analysis methods and techniques in research projects. *International Journal of Academic Research in Management, 9*(1), 1–9. https://hal.science/hal-03741837/

Tarawneh, M. M. A., Nguyen, T. P. L., Yong, D. G. F., & Dorasamy, M. A. P. (2023). Determinant of m-banking usage and adoption among millennials. *Sustainability, 15*(10), Article 8216. https://doi.org/10.3390/su15108216

The Story Thailand. (2023, November 10). *Google: Thailand's digital economy ranks second in Southeast Asia.* https://www.thestorythailand.com/en/10/11/2023/116583/

Thomas, D., & Zubkov, P. (2023). Quantitative research designs. In P. Činčala, D. Penno, P. Zubkov, & S. Wa-Mbaleka (Eds.), *Quantitative research for practical theology* (pp. 103–114). Department of World Mission, Andrews University and Avondale Academic Press. https://www.researchgate.net/publication/370630979

Uakarn, C., Chaokromthong, K., & Sintao, N. (2021). Sample size estimation using Yamane and Cochran and Krejcie and Morgan and green formulas and Cohen statistical power analysis by G*Power and comparisons. *APHEIT International Journal of Interdisciplinary Social Sciences and Technology, 10*(2), 76–88. https://so04.tci-thaijo.org/index.php/ATI/article/view/254253

Uthaileang, W., & Kiattisin, S. (2023). Developing the capability of digital financial literacy in developing countries: A case of online loan for small entrepreneurs. *Heliyon, 9*(12), Article e21961. https://doi.org/10.1016/j.heliyon.2023.e21961

Veling, J. (2025, June 27). *How do debt consolidation loans work?* NerdWallet. https://www.nerdwallet.com/article/loans/personal-loans/how-do-debt-consolidation-loans-work

Wang, P., Zheng, H., Chen, D., & Ding, L. (2015). Exploring the critical factors influencing online lending intentions. *Financial Innovation, 1,* Article 8. https://doi.org/10.1186/s40854-015-0010-9

Widener, K. N. (2017). Financial management issues of college-aged students: Influences and consequences. *Selected Honors Theses,* Article 63. http://firescholars.seu.edu/honors/63

Xia, L., Baghaie, S., & Sajadi, S. M. (2023). The digital economy: Challenges and opportunities in the new era of technology and electronic communications. *Ain Shams Engineering Journal, 15*(2), Article 102411. https://doi.org/10.1016/j.asej.2023.102411

APPENDIX. QUESTIONNAIRE

Section A: Demographic information

What is your gender?
☐ Male
☐ Female

What is your age?
☐ Under 20
☐ 21–30
☐ 31–40
☐ 41–50
☐ Over 50

What is your highest level of education?
☐ Primary school
☐ Secondary school
☐ Bachelor's degree
☐ Master's degree or higher

Are you currently a student?
☐ Yes
☐ No

Where do you currently reside?
☐ Bangkok and vicinity
☐ Other provinces

Section B: Financial behavior

What is your average monthly income (in THB)?
☐ Less than 10,000
☐ 10,001–20,000
☐ 20,001–30,000
☐ 30,001–40,000
☐ Above 40,000

What is your average monthly expense (in THB)?
☐ Less than 10,000
☐ 10,001–20,000
☐ 20,001–30,000
☐ 30,001–40,000
☐ Above 40,000

What is your average monthly savings (in THB)?
☐ None
☐ Less than 5,000
☐ 5,001–10,000
☐ Above 10,000

Do you have any existing monthly debt obligations?
☐ Yes
☐ No

How frequently do you perform digital financial transactions?
☐ Never
☐ Rarely
☐ Sometimes
☐ Often
☐ Very often

Section C: Perceptions of digital lending platforms

(Please rate your agreement with the following statements on a scale of 1 to 5, where 1 = Strongly Disagree and 5 = Strongly Agree)

I am interested in borrowing money through applications.□ □ □ □ □
I am aware of the terms and conditions of borrowing money through applications. □ □ □ □ □
I compare multiple loan apps before deciding which one to use. □ □ □ □ □
I believe the interest rates on loan applications are reasonable. □ □ □ □ □
I think there are no hidden charges or additional fees. □ □ □ □ □
I find the digital lending application easy to use. □ □ □ □ □
I feel confident about the security of loaning money through an application. □ □ □ □ □
I am concerned about the misuse of my personal data when using loan applications. □ □ □ □ □
Loaning through applications makes financial transactions more convenient for me. □ □ □ □ □
I am satisfied with my experience using digital lending applications. □ □ □ □ □
I would recommend digital lending applications to others. □ □ □ □ □

Section D: Digital financial awareness

Have you read and understood digital lending terms and conditions before applying for a loan?
□ Yes
□ No

Where do you usually get information about digital lending services? (Select all that apply)
□ Social media
□ Friends or family
□ Financial institutions' websites
□ Loan apps
□ News media
□ Others (please specify): _____

Section E: Adoption intention

Have you ever used a digital lending platform (e.g., app or website) to borrow money?
□ Yes
□ No

If not, are you willing to consider using digital lending in the future?
□ Yes
□ No
□ Not sure