“Examining determinants of loan default: An empirical analysis on credit factors in Thai savings and credit cooperatives”

AUTHORS	Klangjai Sangwichitr Panern Intara

ARTICLE INFO	Klangjai Sangwichitr and Panern Intara (2024). Examining determinants of loan default: An empirical analysis on credit factors in Thai savings and credit cooperatives. *Investment Management and Financial Innovations*, *21*(4), 323-332. doi:10.21511/imfi.21(4).2024.26
DOI	http://dx.doi.org/10.21511/imfi.21(4).2024.26
RELEASED ON	Monday, 25 November 2024
RECEIVED ON	Tuesday, 17 September 2024
ACCEPTED ON	Thursday, 14 November 2024

JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
38	0	4

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Klangjai Sangwichitr (Thailand), **Panern Intara** (Thailand)

EXAMINING DETERMINANTS OF LOAN DEFAULT: AN EMPIRICAL ANALYSIS ON CREDIT FACTORS IN THAI SAVINGS AND CREDIT COOPERATIVES

Abstract

Savings and credit cooperatives (SACCOs) are crucial institutions in promoting financial accessibility. SACCOs provide financial loans to individuals who may not have access to traditional banking. SACCOs take their own risk to get loan defaults from the offerings because member loans are approved without checking the members' credit background by SACCO committees. This study aims to investigate factors influencing loan defaults of savings and credit cooperatives in Thailand. Based on the savings and credits cooperative database in November 2023, the cooperative has emergency loans, regular loans, and special loans totaling 11,441 contracts. In this study, all loan contracts of this cooperative were used to analyze. The data were divided into two categories of debt classification, including (1) non-default status and (2) default status. The data were analyzed using logistics regression to select the highest accuracy model. Furthermore, the finding reveals that the highest accuracy model, at 99.78%, contains five variables, including interest rate, collateral value, remaining contract duration, outstanding debt, and installment amount. The savings and credit cooperatives institution should adjust the loan interest rates according to economic conditions. Moreover, closely monitoring members with high remaining debt would help the institution prevent loan defaults, and the institution should also create a conservative loan approval policy to reduce its loan default.

Received on: 17th of September, 2024
Accepted on: 14th of November, 2024
Published on: 25th of November, 2024

Klangjai Sangwichitr, D.B.A., Assistant Professor of Business Administration, Department of Business Administration, Faculty of Management Sciences, Prince of Songkla University, Thailand.

Panern Intara, M.B.A., Department of Business Administration, Faculty of Management Sciences, Prince of Songkla University, Thailand. (Corresponding author)

Keywords loan default, savings and credit cooperatives, financial institution, logistic regression, Thailand

JEL Classification G17, G23, G51

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

Savings and credit cooperatives (SACCOs) provide financial services to individuals who may not have access to traditional banking (Assawawongsathien et al., 2017), support economic expansion (Namwong & Janyasuprab, 2018; Sfar & Ben Ouda, 2016), and enhance the financial welfare of their members and communities (Keawmanee, 2016). Changes in interest rate policy announced by the Bank of Thailand (BOT) directly impact the investment opportunities of savings and credit cooperatives in several ways, such as higher borrowing costs and pressure on loan demand. Higher interest rates may reduce the demand for loans from cooperative members, potentially impacting the cooperatives' revenues and growth prospects. Although large SACCOs have various investment opportunities that can generate reasonable returns, it cannot be denied that lending to its members for various purposes remains a significant source of revenue and profit for the cooperative. Due to the significant roles of SACCOs for their members, communities, and the economy, any financial instability experienced by SACCOs would not only disrupt their functioning but also have consequences for the community, economy, and all members' financial stability. The default risk of SACCOs refers to the probability that borrowers within the cooperative will fail to repay their loans as agreed. The financial health of SACCOs is heavily dependent on the repayment behavior of their members (McKillop et al., 2020). High default rates may gradually weaken a cooperative's financial stability, resulting in financial losses that impact all members.

1. LITERATURE REVIEW AND HYPOTHESES

Understanding the factors influencing member debt repayment behaviors is crucial for developing effective credit analysis strategies, thereby reducing NPL risks. Implementing credit scoring as a statistical tool for credit analysis can enhance loan consideration efficiency and help mitigate long-term NPLs for the cooperative.

In the 19th century, the first saving and credit cooperatives were established in Germany by Herman Schultze-Delitsche and Freidrich Reifeisen. Then Luigi adopted the principles of the German saving and credit cooperatives and established the first saving and credit cooperatives in Italy. After that saving and credit cooperatives principles were well known and were established by labor unions and organizations around the world (Galor, 1999). In Thailand, SACCOs were established to promote savings and loans to a group of people who are in the same organization (Cooperative Promotion Department, 2021). In SACCOs, funds are raised from owners' capital, and the owners get dividends in return every year based on the cooperatives' performance. The SACCOs' uses of funds come from their investment and loan interest payments, which would create their performance (Galor, 1999). The SACCOs with good structure and financial capital may have better performance (Laliwan & Potipiroon, 2022). However, board committees would be the key people who make short- and long-term regulations (Kaplan & Mccay, 2004). The SACCO provides credit to its members to create income by receiving full repayment and interest payments.

SACCOs were established to help their members promote savings and to provide loans to members when needed (Galor, 1999; Omeke et al., 2019; Laliwan & Potipiroon, 2022). In Thailand, there are 3 loan categories offered by savings and credit cooperatives, including emergency loans, general loans, and special loans (Cooperative Promotion Department, 2021). The SACCOs being discussed have a large internal cash surplus (The Savings and Credits Cooperatives, 2023). This cash flow presents both opportunities and challenges for the cooperative. If the cooperative cannot find sufficient investment opportunities to cover its cost of capital – including the cost of debt (interest payments) and the cost of equity (dividends) – or if it takes an overly conservative approach to investment or credit analysis, its revenue generation and long-term profitability might be adversely affected. Conversely, if the cooperative adopts an aggressive investment strategy, it might increase revenue but also face higher risks amid rising interest rates, potentially leading to an increase in non-performing loans (NPLs). The Civil and Commercial Code B.E. 2535 defined loan defaults as any contract owner who fails to make their payment by the due date. On the other hand, Cooperative Auditing Department (2016) defines loan default as any contact owner who fails to pay the principal or interest within 1-60 days from the date. It means that if the debtor fails to make a payment for more than 60 days, the contract would be defined as loan default. The prediction model can be used as a tool promoting a warning system and ensuring an organization's financial stability (Hammond et al., 2023).

Credit Scoring is a statistical analysis of a borrower's historical debt repayment information and behavior. Financial institutions use credit scoring to perform a predictive model assessing the likelihood of repaying a loan for a new loan application. This analysis evaluates the current situation of the loan applicant, including personal data, financial data, and historical repayment records (Onay & Öztürk, 2018; Petrides et al., 2022; Van Gool et al., 2012). Credit scoring plays a critical role in finance and banking as it allows lenders to have a better understanding of borrowers by predicting the likelihood of future loan repayments. Moreover, this score reflects the economic credibility of an individual and is used as part of the loan approval process. Thus, this scoring is a risk management tool used to

http://dx.doi.org/10.21511/imfi.21(4).2024.26

evaluate the credibility of borrowers (Boughaci & Alkhawaldeh, 2019). It is important to find factors for model predictions used as credit scoring.

There is much research focusing on seeking credit factors influencing loan defaults (Steenackers & Goovaerts, 1989; Nguyen, 2015; Bravo et al., 2015; Barua et al., 2021; Saha et al., 2023; Thomas et al., 2023; Abdou et al., 2017; Lokesha & Hawaldar, 2019). The results reveal that borrower characteristics, the down payment rate, credit term, remaining contract term, interest rate, and approved loan amount impact the probability of loan default. In Thailand, Pattarapornpairot (2020) studied the variables influencing loan default prediction, including the approved loan amount, remaining contract term, interest rate, outstanding debt, and collateral. Similarly, Notanonda (2000) investigated factors leading to default on residential loans at a commercial bank in Chiang Mai, finding that income and the borrower's age were key predictors, aligning with Chushim's (2013) study on factors affecting non-performing loans (NPLs) for housing loans, which highlighted age, income, debt-to-income ratio, loan-to-value ratio, and monthly installments as significant factors.

In addition, there are many methods in order to create prediction models (Zhu, 2019; Zhu et al., 2023; Nguyen, 2015; Sariannidis et al., 2023) such as Decision tree, Random forest, Neural networks, K nearest Neighbor, Logistic regression, XGBoost, and LightGBM. Ali Albastaki (2022) proved that Logistic Regression is the best model for a loan default prediction system. Research constructing loan default prediction models typically utilizes Logistic Regression statistics as in commercial bank, student loan, and public mortgage loans; the results reveal that factors affecting loan repayment are approved loan amount, remaining contract term, collateral, interest rate, and outstanding debt as influential (Thiansomboon, 2017; Imsuk, 2018; Kamphod, 2019; Maichandrang, 2021) In other countries, mortgage loan default can be predicted from interest rate and monthly payments (ANTAR, 2024).

The purpose of the study is to seek factors influencing loan defaults among the members of the savings and credit cooperatives in Thailand. The research hypotheses are formulated as follows:

H_1: *The loan interest rate impacts the repayment status.*

H_2: *The collateral value impacts the repayment status.*

H_3: *The approved loan amount impacts the repayment status.*

H_4: *The remaining contract duration impacts the repayment status.*

H_5: *The outstanding debt impacts the repayment status.*

H_6: *The monthly installment impacts the repayment status.*

2. RESEARCH METHODOLOGY

Based on the literature review, this study's independent variables are loan interest rate, collateral value, the approved loan amount, remaining contract duration, outstanding debt, and monthly installment. The dependent variable is the repayment status, which represents the loan defaults. Logistic regression analysis is used to analyze data.

This study collected data from the database of a large savings and credit cooperative whose assets exceeded 30,000 million Thai baht in November 2023. The analysis utilized all contracts from this cooperative, totaling 11,441 contracts. The data were divided into two categories of debt classification: (1) non-default status and (2) default status.

This study divided the data into two parts: part (1) 80% proportion, totaling 9,163 contracts, was selected using accidental sampling. This includes 8,973 contracts with non-default status and 190 contracts with default status. Part (2) 20% proportion, totaling 2,287 contracts, was also selected using accidental sampling. This includes 2,222 contracts with non-default status and 56 contracts with default status. Data were randomly selected from debtors across the two categories of debt classification. Part (1) was used for model creation by logistic regression analysis, while part (2) was used to validate the model's accuracy. Table 1 shows the proportion of 80% and 20% samples categorized by research variables, including the approved loan interest rate, collateral value, approved loan amount, remaining contract duration, outstanding debt, and monthly installment.

The first part of the study analyzes the factors affecting loan default among the savings and credit cooperatives members, using data from November 2023, representing 80% of the sample. The analysis is conducted using logistic regression models with six variables: loan interest rate (Int), collateral value (Col), approved loan amount (Vol), remaining contract duration (Term), outstanding debt (Loan), and monthly installment (Pay), with loan status (Y) as the dependent variable. Six different models are analyzed:

Model 1 uses all six variables:

$$Y = \beta_0 + \beta_1 Int + \beta_2 Col + \beta_3 Vol + \beta_4 Term + \beta_5 Loan + \beta_6 Pay. \quad (1)$$

Model 2 uses five variables, excluding the approved loan amount (Vol):

$$Y = \beta_0 + \beta_1 Int + \beta_2 Col + \beta_3 Term + \beta_4 Loan + \beta_5 Pay. \quad (2)$$

Model 3 uses four variables, excluding the approved loan amount (Vol) and collateral value (Col):

$$Y = \beta_0 + \beta_1 Int + \beta_2 Term + \beta_3 Loan + \beta_4 Pay. \quad (3)$$

Model 4 uses three variables, excluding the approved loan amount (Vol), collateral value (Col), and outstanding debt (Loan):

$$Y = \beta_0 + \beta_1 Int + \beta_2 Term + \beta_3 Pay. \quad (4)$$

Model 5 uses three variables, excluding the approved loan amount (Vol), collateral value (Col), and monthly installment (Pay):

Table 1. Sample loan data from the savings and credit cooperatives, divided by 80% and 20% proportions, by variable

Variables	Proportion of 80%				Proportion of 20%			
	Non-default		Default		Non-default		Default	
	Frequency (total of 8,973)	Proportion	Frequency (total of 190)	Proportion	Frequency (total of 2,222)	Proportion	Frequency (total of 56)	Proportion
Loan interest rate (Int)								
3.95%-10.47%	8,971	0.9998	170	0.8947	2,222	1.0000	47	0.8393
10.48%-17%	2	0.0002	20	0.1053	0	0.0000	9	0.1607
Collateral (Col)								
Less than 1,000,000	7,431	0.8282	134	0.7053	1,848	0.8317	36	0.6429
1,000,000 – 5,000,000	1,482	0.1652	51	0.2684	361	0.1625	18	0.3214
More than 5,000,000	60	0.0067	5	0.0263	13	0.0059	2	0.0357
Approved loan amount (Vol)								
Less than 1,000,000	6,790	0.7567	125	0.6579	1,698	0.7642	34	0.6071
1,000,000 – 5,000,000	2,122	0.2365	60	0.3158	510	0.2295	20	0.3571
More than 5,000,000	61	0.0068	5	0.0263	14	0.0063	2	0.0357
Remaining contract duration (Term)								
Less than 1,000,000	3,881	0.4325	73	0.3842	949	0.4271	16	0.2857
1,000,000 – 5,000,000	1,852	0.2064	68	0.3579	456	0.2052	22	0.3929
More than 5,000,000	3,240	0.3611	49	0.2579	817	0.3677	18	0.3214
Outstanding debt (Loan)								
Less than 1,000,000	7,761	0.8649	151	0.7947	1,928	0.8677	42	0.7500
1,000,000 – 5,000,000	1,185	0.1321	35	0.1842	290	0.1305	12	0.2143
More than 5,000,000	27	0.0030	4	0.0211	4	0.0018	2	0.0357
Monthly installment (Pay)								
Less than 10,000	7,451	0.8304	154	0.8105	1,831	0.2041	44	0.7857
10,001 – 25,000	1,294	0.1442	28	0.1474	346	0.0386	9	0.1607
25,001 – 40,000	172	0.0192	4	0.0211	35	0.0039	1	0.0179
More than 40,000	56	0.0062	4	0.0211	10	0.0011	2	0.0357

http://dx.doi.org/10.21511/imfi.21(4).2024.26

$$Y = \beta_0 + \beta_1 Int + \beta_2 Term + \beta_3 Loan. \quad (5)$$

Model 6 uses five variables, excluding the monthly installment (Pay):

$$Y = \beta_0 + \beta_1 Int + \beta_2 Col + \beta_3 Vol + \beta_4 Term + \beta_5 Loan. \quad (6)$$

3. RESULTS

The correlation coefficients between the six variables are used to observe the direction of the relationship between the two variables. The correlation coefficients of the variables are presented in Table 2.

Table 2, displayed the correlation coefficients between the variables, shows the following significant relationships: collateral value (Col) is positively correlated with the approved loan amount (Vol) (r = .798**), outstanding debt (Loan) (r = .632**), and installment amount (Pay) (r = .629**). Moreover, the approved loan amount (Vol) is positively correlated with the outstanding debt (Loan) (r = .713**) and installment amount (Pay) (r = .677**). Finally, the remaining contract duration (Term) is positively correlated with the outstand-

Table 2. Correlation coefficients of predictive variables

Variable	Correlation and P-value	Int	Col	Vol	Term	Loan	Pay
Int	Pearson Correlation	1	.006	–.003	–.014	.006	.012
	Sig. (2-tailed)	–	.594	.792	.193	.581	.266
Col	Pearson Correlation	.006	1	.798**	.005	.632**	.629**
	Sig. (2-tailed)	.594	–	0.000	.647	0.000	0.000
Vol	Pearson Correlation	–.003	.798**	1	–.007	.713**	.677**
	Sig. (2-tailed)	.792	0.000	–	.512	0.000	0.000
Term	Pearson Correlation	–.014	.005	–.007	1	.022*	–.101**
	Sig. (2-tailed)	.193	.647	.512	–	.037	.000
Loan	Pearson Correlation	.006	.632**	.713**	.022*	1	.659**
	Sig. (2-tailed)	.581	0.000	0.000	.037	–	0.000
Pay	Pearson Correlation	.012	.629**	.677**	–.101**	.659**	1
	Sig. (2-tailed)	.266	0.000	0.000	.000	0.000	–

Notes: ** Correlation is significant at the 0.01 level (2-tailed), and * Correlation is significant at the 0.05 level (2-tailed).

Table 3. Results of logistic regression analysis of variables leading to loan default

Variables	Coefficient and S.E.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	Coefficient	–11.074	–11.065	–10.777	–10.347	–10.845	–11.109
	S.E.	0.823	0.822	0.816	0.804	.816	0.824
Int	Coefficient	6.371**	6.365**	6.306**	6.252**	6.283**	6.313**
	S.E.	0.75	0.75	0.748	0.746	.748	0.749
	Exp(B)	584.778	581.422	547.952	518.904	535.913	551.733
Col	Coefficient	0.885**	0.934**	–	–	–	0.743*
	S.E.	0.316	0.222	–	–	–	0.314
	Exp(B)	2.422	2.545	–	–	–	2.103
Vol	Coefficient	0.073	–	–	–	–	–0.085
	S.E.	0.33	–	–	–	–	0.329
	Exp(B)	1.075	–	–	–	–	0.918
Term	Coefficient	–0.097	–0.097	–0.073	–0.032	–.050	–0.048
	S.E.	0.093	0.093	0.091	0.088	.090	0.091
	Exp(B)	0.907	0.907	0.93	0.969	.951	0.953
Loan	Coefficient	0.382	0.401	0.865**	–	–	0.089
	S.E.	0.278	0.267	0.254	–	–	0.259
	Exp(B)	1.465	1.493	2.376	–	–	1.093
Pay	Coefficient	–0.596**	–0.59**	–0.31	0.156	0.584**	–
	S.E.	0.215	0.213	0.211	0.142	.176	–
	Exp(B)	0.551	0.554	0.734	1.169	1.795	–
Nagelkerke R Square	–	0.102	0.102	0.092	0.086	.091	0.097

ing debt burden (Loan) (r = .022**) but negatively correlated with the installment amount (Pay) (r = -.101**), with a significance level of 0.01.

Base on Table 3, the models are formulated as follows:

Model 1 uses all six variables:

$$Y = -11.074 + 6.371 Int + 0.885 Col + 0.073 Vol - 0.097 Term + 0.382 Loan - 0.596 Pay. \tag{7}$$

Model 2 uses five variables, excluding the approved loan amount (Vol):

$$Y = -11.065 + 6.365 Int + 0.934 Col - 0.097 Term + 0.401 Loan - 0.59 Pay. \tag{8}$$

Model 3 uses four variables, excluding the approved loan amount (Vol) and collateral value (Col):

$$Y = -10.777 + 6.306 Int - 0.073 Term + 0.865 Loan - 0.31 Pay. \tag{9}$$

Model 4 uses three variables, excluding the approved loan amount (Vol), collateral value (Col), and outstanding debt (Loan):

$$Y = -10.347 + 6.252 Int - 0.032 Term + 0.156 Pay. \tag{10}$$

Model 5 uses three variables, excluding the approved loan amount (Vol), collateral value (Col), and monthly installment (Pay):

$$Y = -10.845 + 6.283 Int - 0.50 Term + 0.584 Loan. \tag{11}$$

Model 6 uses five variables, excluding the monthly installment (Pay):

$$Y = -11.109 + 6.313 Int + 0.743 Col - 0.085 Vol - 0.048 Term + 0.089 Loan. \tag{12}$$

Table 3 reveals that at a significance level of 0.01, the interest rate (Int) significantly affects loan default probability across all models, with coefficients of 6.371, 6.365, 6.306, 6.252, 6.283, and 6.313, respectively, and odds ratios of 584.778, 581.422, 547.952, 518.904, 535.913, and 551.733, respectively. The coefficient and odds ratio of Model 1 can be explained as a coefficient of 6.371; this means that a 1% increase in the interest rate increases the probability of loan default by 6.371 times. Moreover, collateral value (Col) is significant at the level of 0.01 in Models 1, 2, and 6 with coefficients and odds ratios: (1) Model 1: coefficient = 0.885, odds ratio = 2.422; (2) Model 2: coefficient = 0.934, odds ratio = 2.545; and (3) Model 6: coefficient = 0.743, odds ratio = 2.103. For Model 1, a coefficient of 0.885 means that a 1,000 THB increase in collateral value increases the probability of loan default by 0.885 times. Outstanding debt (Loan) is significant at the level of 0.01 in Model 3 with a coefficient of 0.865 and an odds ratio of 2.375. Installment amount (Pay) is significant at the level of 0.01 in models 1, 2, and 5 with coefficients and odds ratios: (1) Model 1: coefficient = −0.596, odds ratio = 0.551; (2) Model 2: coefficient = −0.59, odds ratio = 0.554; and (3) Model 5: coefficient = 0.584, odds ratio = 1.795. For Model 1, a coefficient of −0.596 means that a 1,000 THB increase in the installment amount decreases the probability of loan default by 0.596 times.

To validate the model's accuracy, the second part of the study predicts loan default using 20% of the sample data, with 2,278 contracts. The prediction uses the logistic regression models to calculate Y for each contract and determine the probability of default. Based on model 1, the model's prediction accuracy is 2.38% when substituting the value into the probability equation (Boateng & Abaye, 2019; Thiansomboon, 2017) as follows.

The result reveals that there were 2,222 non-default contracts; the equation correctly predicted 53 contracts. For the loan defaults of 56 contracts, the equation correctly predicted 1 contract. This means that a total of 2,278 contracts were used to

$$P_{(loan\ defaults)} = \frac{e^{-11.074 + 6.371 Int + 0.885 Col + 0.073 Vol - 0.097 Term + 0.382 Loan - 0.596 Pay}}{1 + e^{-11.074 + 6.371 Int + 0.885 Col + 0.073 Vol - 0.097 Term + 0.382 Loan - 0.596 Pay}}. \tag{13}$$

http://dx.doi.org/10.21511/imfi.21(4).2024.26

Table 4. Result validation

Model	Non-default				Default			
	Correct		Incorrect		Correct		Incorrect	
	Frequency	Proportion	Frequency	Proportion	Frequency	Proportion	Frequency	Proportion
Model 1	53	0.0238	2,169	0.9762	1	0.0238	55	0.9762
Model 2	2,217	0.9978	5	0.0022	56	0.9978	0	0.0022
Model 3	1,841	0.8285	381	0.1715	46	0.8285	10	0.1715
Model 4	1,684	0.7581	538	0.2419	42	0.7581	14	0.2419
Model 5	967	0.4350	1,255	0.5650	24	0.4350	32	0.5650
Model 6	1,933	0.8700	289	0.1300	49	0.8700	7	0.1300

validate the model; Model 1 correctly predicted 54 contracts, as shown in Table 4.

According to the validation method used in Model 1, the equation correctly predicted 2,217 non-default accounts and 56 default accounts. Out of the 2,278 accounts used for validation, the model correctly predicted 2,273 accounts, resulting in an accuracy of 99.78% in Model 2. The result confirms that H_3 is not a predictor for the loan default.

For Model 3, the equation correctly predicted 1,841 non-default accounts and 46 default accounts. Out of the 2,278 accounts used for validation, the model correctly predicted 1,887 accounts, resulting in an accuracy of 82.85%. The equation correctly predicted 1,684 non-default accounts and 42 default accounts. Out of the 2,278 accounts used for validation, the model correctly predicted 1,727 accounts, resulting in an accuracy of 75.81% in Model 4.

For Model 5, the equation correctly predicted 967 non-default accounts and 24 default accounts. Out of the 2,278 accounts used for validation, the model correctly predicted 991 accounts, resulting in an accuracy of 43.50%.

Finally, the equation correctly predicted 1,933 non-default accounts and 49 default accounts. Out of the 2,278 accounts used for validation, the model correctly predicted 1,982 accounts, resulting in an accuracy of 87.00% in Model 6.

Thus, Model 2 provides the highest accuracy at 99.78%, suggesting it is the most accurate for predicting loan default with the five variables: interest rate (H_1), collateral value (H_2), remaining contract duration (H_4), remaining debt (H_5), and monthly installment (H_6).

4. DISCUSSION

This study's logistics regression result reveals that loan default can be predicted by interest rate, collateral value, remaining contract duration, outstanding debt, and monthly installment. The result aligns with the study by Tiensomboon (2017) on factors affecting housing loan defaults, indicating that the significant factors are consistent across different types of loan analyses. Moreover, the variables used as loan default predictors align with many previous studies, such as Barua et al. (2021), Omek et al. (2023), Saha et al. (2023), and Thomas et al. (2023), which all concluded that credit term, interest rate, outstanding debt, impact significantly to the probability of loan default. One possible explanation for the findings' consistency with many previous studies is that, despite the fact that savings and credit cooperatives differ from commercial banks in that they exclusively offer their loan to members, the credit analysis procedures of these financial institutions should be identical to those of commercial banks. Crucial factors such as interest rate, outstanding debt, credit term all need to be carefully considered. The result on interest rate can be a predictor for loan default. A loan contract with a higher interest rate would have a higher monthly loan payment than a contract with a lower interest rate, reflecting the higher opportunity of loan default. If a borrower has liquidity issues, he or she will not be able to repay the loan. Moreover, high collateral value and high outstanding debt balance will cause loan default since it would be difficult for a borrower to make a repayment in case of insufficient liquidity. On the other hand, a shorter contract duration makes a lower risk of loan default because the outstanding debt is not as high as when the contract begins. Moreover, the higher monthly installments reflect the borrower's good financial stability, then the likelihood of loan default would be avoided.

The limitations of this study are that, first, it is difficult to collect time series data from the database. Second, this study implies only the Logistics Regression method to create a prediction model. Future studies should consider time series data analysis and compare several models to confirm predictions.

CONCLUSION

The study aims to investigate factors influencing loan defaults among the members of the savings and credit cooperatives in Thailand. The finding reveals that the highest accuracy factors are interest rate, collateral value, remaining contract duration, outstanding debt, and installment amount. The savings and credits cooperative institution should adjust the loan interest rates according to economic conditions. Moreover, closely monitoring members with high remaining debt would help the institution prevent loan defaults, and the institution should create a conservative loan approval policy to reduce its loan default. Moreover, the prediction results benefit stakeholders such as the savings and credit cooperatives institution, microfinance institutions, and regulators. The savings and credit cooperatives institution should adjust the loan interest rates according to economic conditions. Moreover, closely monitoring members with high outstanding debt would help the institution prevent loan defaults. On the other hand, the institution should create a conservative loan approval policy, such as considering the appropriateness of the loan amount relative to collateral value, increasing monthly installment for loans without collateral to reduce default probability, and extending repayment periods for loans with collateral to reduce default probability.

AUTHOR CONTRIBUTIONS

Conceptualization: Klangjai Sangwichitr, Panern Intara.
Data curation: Klangjai Sangwichitr.
Formal analysis: Klangjai Sangwichitr, Panern Intara.
Investigation: Klangjai Sangwichitr, Panern Intara.
Methodology: Klangjai Sangwichitr, Panern Intara.
Project administration: Panern Intara.
Supervision: Klangjai Sangwichitr, Panern Intara.
Validation: Panern Intara.
Visualization: Klangjai Sangwichitr.
Writing – original draft: Klangjai Sangwichitr, Panern Intara.
Writing – review & editing: Klangjai Sangwichitr, Panern Intara.

ACKNOWLEDGMENTS

The research for the work featured in this article is funded by the Prince of Songkla Savings and Credit Cooperatives, Limited.

REFERENCES

1. Abdou, H., Abdallah, W., Mulkeen, J., Ntim, C., & Wang, Y. (2017). Prediction of financial strength ratings using machine learning and conventional techniques. *Investment Management and Financial Innovations,* 14(4), 194-211. https://doi.org/10.21511/imfi.14(4).2017.16
2. Ali Albastaki, A. (2022). *Loan Default Prediction System. Thesis. Rochester Institute of Technology.* Retrieved from https://repository.rit.edu/cgi/viewcontent.cgi?article=12544&context=theses
3. Antar, M. (2024). Evaluating the Impact of Borrower Characteristics, Loan Specific Parameters, and Property Conditions on Mortgage Default Risk. *Theoretical and Practical Research in Economic Fields, 15*(2), 481-501. https://doi.org/10.14505/tpref.v15.2(30).24
4. Assawawongsathien, S., Srichart, K., & Nudam, R. (2017). *The role*

and risks of the savings cooperative system. Puey Ungphakorn Institute for Economic Research. Thailand: Bangkok.

5. Barua, S., Gavandi, D., Sangle, P., Shinde, L., & Ramteke, J. (2021). Swindle: Predicting the Probability of Loan Defaults using CatBoost Algorithm. *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 1710-1715). Erode, India. https://doi.org/10.1109/ICCMC51019.2021.9418277

6. Boateng, E., & Abaye, D. (2019). A Review of the Logistic Regression Model with Emphasis on Medical Research. *Journal of Data Analysis and Information Processing, 11*(4), 190-207. https://doi.org/10.4236/jdaip.2019.74012

7. Boughaci, D., & Alkhawaldeh, A. A. (2019). A cooperative classification system for credit scoring. Smart Technologies and Innovation for a Sustainable Future. *Proceedings of the 1st American University in the Emirates International Research Conference* (pp. 11-20). Dubai, UAE. https://doi.org/10.1007/978-3-030-01659-3_2

8. Bravo, C., Thomas, L. C., & Weber, R. (2015). Improving credit scoring by differentiating defaulter behavior. *Journal of the Operational Research Society, 66*(5), 771-781. https://doi.org/10.1057/jors.2014.50

9. Chushim, K. (2013). *Factors causing the non-performing loans on housing-loan of a commercial bank.* Thammasat University. Retrieved from https://digital.library.tu.ac.th/tu_dc/frontend/Info/item/dc:97119

10. Cooperative Auditing Department. (2016). *The Registrar of Cooperatives Regulations on the Classification of Loan Quality and the Provision for Doubtful Debts.* Retrieved from https://www.cad.go.th/ewt_dl_link.php?nid=30451&filename=regul2_05_1

11. Cooperative Promotion Department. (2021). *Background.* Retrieved from https://cpd.go.th/knowledge/general-coop.html

12. El Hancha Sfar, F., & Ben Ouda, O. (2016). Contribution of Cooperative Banks to the Regional Economic Growth: Empirical Evidence from France. *International Journal of Economics and Financial Issues,* 6(2), 508-514. Retrieved from https://www.econjournals.com/index.php/ijefi/article/view/1750

13. Galor, Z. (1999). *Credit and Saving Cooperatives: A new conceptual approach.* Retrieved from https://www.findevgateway.org/sites/default/files/publications/files/mfg-en-paper-saving-and-credit-cooperatives-a-new-conceptual-approach-2003.pdf

14. Hammond, P., Opoku, M., Kwakwa, P., & Amissah, E. (2023) Predictive models of going concerns and business failure. *Cogent Business & Management,* 10(2), 1-24. https://doi.org/10.1080/23311975.2023.2226481

15. Imsuk, S. (2018). *Factors affecting the credit default for the loan of the land bank administration institute (public organization).* Thamasat University. Retrieved from https://digital.library.tu.ac.th/tu_dc/frontend/Info/item/dc:142217

16. Kamphod, K. (2019). *Factors Affecting the Default on Student Loan Fund (SLF) in Thailand.* Chaing Mai University. Retrieved from https://cmudc.library.cmu.ac.th/frontend/Info/item/dc:143095

17. Kaplan, I., & Mccay, B. (2004). Cooperative research, co-management and the social dimension of fisheries science and management. *Marine Policy, 28,* 257-258. https://doi.org/10.1016/j.marpol.2003.08.003

18. Keawmanee, S. (2016). *The Role of Cooperatives in Economic and Social Development by Members of Thanto Agricultural Cooperatives Limited, Yala Province.* Bangkok: Sukhothai Thammathirat Open University. Retrieved from https://ir.stou.ac.th/handle/123456789/5470

19. Laliwan, S., & Potipiroon, W. (2022). Board Capital, Organizational Capital and Organizational Performance of Agricultural and Non-agricultural Co-operatives in Thailand. *ABAC Journal, 42*(2), 195-215. https://doi.org/10.14456/abacj.2022.11

20. Lokesha, & Hawaldar, I. (2019). Impact of factors on the utilization of agricultural credit of banks: an analysis from the borrowers' perspective. *Banks and Bank Systems, 14*(1), 181-192. https://doi.org/10.21511/bbs.14(1).2019.16

21. Maichandrang, S. (2021). *An Analysis of debt default probability of bank client: A Case study of teacher and local government of Krung Thai Bank, Hod Branch.* Chaing Mai University. Retrieved from http://cmuir.cmu.ac.th/jspui/handle/6653943832/73697

22. McKillop, D., French, D., Quinn, B., Sobiech, A. L., & Wilson, J. S. (2020). Cooperative financial institutions: A review of the literature. *International Review of Financial Analysis, 71,* 1-11. https://doi.org/10.1016/j.irfa.2020.101520

23. Namwong, S., & Janyasuprab, P. (2018). The Roles of Thai Cooperatives in New Economic Age. *Walailak Journal of Social Science, 11*(1), 143-183. Retrieved from https://so06.tci-thaijo.org/index.php/asi/article/view/110702/86746

24. Nguyen, H. T. (2015). *How is credit scoring used to predict default in China?* (EconomiX Working Papers 2015-1). University of Paris Nanterre, EconomiX. Retrieved from https://ideas.repec.org/p/drm/wpaper/2015-1.html

25. Notananda, V. (2000). *Factors causing defaults on housing-loan repayment of a commercial bank in Muang district, Chiang Mai Province.* Chiang Mai University. Retrieved from http://repository.cmu.ac.th/handle/6653943832/21665

26. Omeke, M., Ngoboka, P., Nkote, I., & Kayongo, I. (2019) The relationship between complexity behavior and enterprise growth: A case of savings and credit cooperatives in Uganda. *Cogent Business & Management, 6*(1), 1-15. https://doi.org/10.1080/23311975.2018.1564421

27. Onay, C., & Öztürk, E. (2018). A review of credit scoring research in the age of Big Data. *Journal of Financial Regulation and Compliance, 26*(3), 382-405. https://doi.org/10.1108/JFRC-06-2017-0054

28. Pattarapornpairot, N. (2020). *Examining the relationship between macroeconomic variables on non-performing loans from commercial banks in Thailand.* Thamasat University. https://doi.org/10.14457/TU.the.2020.826

29. Petrides, G., Moldovan, D., Coenen, L., Guns, T., & Verbeke, W. (2022). Cost-sensitive learning for profit-driven credit scoring. *Journal of the Operational Research Society, 73*(2), 338-350. https://doi.org/10.1080/01605682.2020.1843975

30. Saha, A., Hock Eam, L., & Goh Yeok, S. (2023). Housing loan default in Malaysia: an analytical insight and policy implications. *International Journal of Housing Markets and Analysis, 16*(2), 273-291. https://doi.org/10.1108/IJHMA-01-2022-0002

31. Sariannidis, N., Papadakis, S., Garefalakis, A., Lemonakis, C., & Kyriaki-Argyro, T. (2020). Default avoidance on credit card portfolios using accounting, demographical and exploratory factors: decision making based on machine learning (ML) techniques. *Annals of Operations Research, 294,* 715-739. https://doi.org/10.1007/s10479-019-03188-0

32. Steenackers, A., & Goovaerts, M. J. (1989). A credit scoring model for personal loans. *Insurance: Mathematics and Economics, 8*(1), 31-34. https://doi.org/10.1016/0167-6687(89)90044-9

33. The Savings and Credit Cooperatives. (2023). *Annual report* 2023. Songkhla: The Prince of Songkla University Savings and Credits Cooperative, Limited. Retrieved from https://psucoop.psu.ac.th/home/ebook_report/detail/17/data.html

34. Thiansomboon, S. (2017). *Factors causing default on housing loan: case study of commercial bank.* Thammasat University. Retrieved from https://digital.library.tu.ac.th/tu_dc/frontend/Info/item/dc:126741

35. Thomas, S. S., George, J. P., Godwin, B. J., & Siby, A. (2023). Young adults' default intention: influence of behavioral factors in determining housing and real estate loan repayment in India. *International Journal of Housing Markets and Analysis, 16*(2), 426-444. https://doi.org/10.1108/IJHMA-01-2022-0012

36. Van Gool, J., Verbeke, W., Sercu, P., & Baesens, B. (2012), Credit scoring for microfinance: is it worth it? *International Journal of Finance & Economics, 17,* 103-123. https://doi.org/10.1002/ijfe.444

37. Zhu, L. (2019). *Predictive Modelling for Loan Defaults*. UCLA. Retrieved from https://escholarship.org/uc/item/3rs9b3d6

38. Zhu, X., Chu, Q., Song, X., Hu, P., & Peng, L. (2023). Explainable prediction of loan default based on machine learning models. *Data Science and Management, 6*(3), 123-133. https://doi.org/10.1016/j.dsm.2023.04.003

http://dx.doi.org/10.21511/imfi.21(4).2024.26