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Predictors of Consumer Creditworthiness: Evidence from Personal Loan Borrowers of a Leading Public Bank in Sri Lanka

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ABSTRACT

Purpose: The motivation of this study is to explore the significant determinants of consumers' creditworthiness which support the development of a credit scoring model as non-performing loans are a major problem in lending institutions.

Design/Methodology/Approach: Data were collected from four branches of a leading Commercial Bank in the Gampaha District under the convenience sampling technique with 130 personal loan borrowers as the study sample.

Findings: The logit model test resulted that age, level of education, and monthly income, are positively influencing the creditworthiness of the borrowers. Increasing the number of dependents and the tenure of the loan have more chances of default. 39% to 56% of the dependent variable was explained by the independent variables in the regression model and the model predicted default correctly by 85.4%.

Originality: The study contributes to the existing literature in terms of identifying important predictors for developing a credit-scoring model while helping lenders to assess the creditworthiness of personal loan applicants. Hence the study will assist in taking effectual measures to enhance the quality of the credit approval process and ultimately reduce the losses of lending institutions from bad debt.

KEYWORDS

Commercial Banks, Creditworthiness, Default Predictors, Sri Lanka

JEL CLASSIFICATION

H81

I. Introduction

"Credit is an amount that is granted by the banks to those applicants who request; this should be repaid at the time including the interest plus principal" (Hand & Henley, 1997, p.2). Consumer credit is a sector of the economy that has grown rapidly over the last 50 years, with banks, merchants, and a variety of other lending institutions providing it. When a creditor correctly predicts an applicant's creditworthiness and default risk using default predictor criteria, they can generate income. Credit scoring is an appropriate method that links these variables to the likelihood of default (Lieli & White, 2010). In the banking sector, personal loan clients demand the loan on a regular basis to meet their life needs. The risk for commercial banks to increase the requested loan depends on how efficiently and accurately differentiates between good borrowers from bad borrowers. So, banks need an organized system that assists them in determining whether to grant credit or not. "Credit Scoring" is the answer to the above problem. Banks employ credit scoring models to evaluate personal loan applications, business loan applications, and credit card applications, and to differentiate high-risk clients /companies from low-risk clients /companies before default. These models are used to evaluate loan applications at various stages of the credit approval process, which can enhance the quality of credit processing, save time and money, improve loan quality, and give banks a competitive advantage. It also controls losses by lowering the number of defaulted loans. To minimize the credit

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risk of individuals and to identify the credit quality of the client, banks need a credit scoring model to evaluate their client's creditworthiness. Otherwise, causing lending institutions to lose money. When a borrower defaults on his or her loans, the banks suffer losses. According to the banking report of Sri Lanka, 2020. The banking sector's non-performing loan ratio has increased by 0.6% (4.8%-5.4%). According to the Leading Banks' (LB) annual report, 2019, the bank has a 2.8% personal loan non-performing ratio among their 3.7% overall non-performing loans and most of the personal loan applicants were represented by western provinces. Hence Non-performing (NP) loans are a major problem in lending institutions.

This study is substantially significant in different ways. Firstly, this study attempts to fill the gap and dearth of research in the Sri Lankan context that can be observed in local literature. Though there are studies considering Accounting, Finance, Market, and governance information on corporate default prediction in broad (Fernando et al., 2022; Lakshan & Wijekoon, 2012), there is no study conducted on unobservable client characteristics and loan-related predictors influencing creditworthiness, which is directly related with nonperforming loans as a proxy of the credit risk. Secondly, discovering these details will enable lending institutions to analyze the credit risk before and after making personal loans by using the identified influencing factors in this study. Thirdly, if a lending institution has a credit scoring model already, it can check whether the unobservable predictors are taken into consideration and modify the model to reduce the number of non-performing loans. Fourthly, when predicting, designing, and developing new credit scoring models, institutions can pay attention to these unobservable characteristics.

Hence the objective of this study is determined as, "To identify the most influential predictors affecting clients' creditworthiness, which will assist the lending institutions to take effectual measures to enhance the quality of the credit approval process. The rest of the sections are organized as literature review, methodology, analysis, discussion and ends with the conclusion.

II. Literature Review and Hypotheses Development

Theoretical Review

Loan default, credit risk, and non-performing loans are expressions with the same connotation which are described as one of the top concerns for banks (Haq, 2010). According to Ford (1988), the reasons for loan default can be classified under three groups: macroeconomic, personal, and psychological. In general, there are several factors including the client's personal behaviours, Loan specific factors, and factors related to credit institutions (Iqbal & Rao, 2022). One of the essential tools developed to minimize such defaults by extracting borrower and loan characters is "credit scoring" to reduce the information asymmetry between the lender (Principal) and the borrower (agent) through which the lender can minimize the liquidity hurdle. Therefore, the study relies on agency theory, originally developed by Jensen and Meckling in 1976 but famously emphasized by Adam Smith in 1776 (Bendicson et al., 2016). The principal-agent theory has a central importance in this study. It is believed that in a contractual agreement between the lender and borrower, the probability of information asymmetry cannot be overlooked. In this regard, the principal-agent theory posits that the principal (lender) does not have complete information and knowledge about the agent (borrowers), and the latter tends to hide important information during the lending process. Both parties also prefer their own interests and targets (Iqbal & Rao, 2022). Therefore, when approving a loan, the principal and agent should be on the same page in the context of information. However, adverse selection and moral hazard make it difficult for the parties (principal and agent) to design an ideal contract. The chances of adverse selection will increase due to the lack of important information about the borrowers, including their financial situation, and character such as age, marital status, level of education, family members, etc. The problem of moral hazard exists when the borrowers do not use the loan amount for the intended purpose and ultimately face loan repayment problems. As a result, the lending decision capacity of the lender will suffer. Hence the study is well-fitted with the agency theory.

Empirical Review and the Development of Hypotheses

A default bank/ financial institution is a place that cannot maintain the sustainability to carry out its operational activities and fulfill its obligations. There are four main risks that can threaten the sustainability of banks/ financial institutions, namely credit risk, market risk, operational risk, and liquidity risk. Non-Performing Loans (NPL) as a proxy of credit risk are losses due to defaults from bank debtors (Fadare, 2011; Puspitasari et al., 2021). Hence lending institutions have started adopting credit scoring models in evaluating personal and business loans as the creditor can make revenues when they successfully predict the creditworthiness and the default risk of applicants depending on the default predictor factors by incorporating the nature of candidates including their demographics and the purpose of which they take the loan, tenure and the amount to classify them in to good and bad (Thomas et al., 2002; Samreen et al., 2013; Lieli &White, 2010; Hendriadi et al., 2018; Chen et al., 2020). Hence client nature plays an important role in credit default and ultimately the success of the financial institutions.

Samreen et al. (2013) built a credit scoring model for Pakistani commercial banks to anticipate the creditworthiness of individual borrowers. The study's major purpose was to examine credit risk in Pakistani commercial banks using credit scoring algorithms. That was the requirement of credit scoring models used by Pakistani commercial banks to judge creditworthiness by using socio-demographic variables. The study resulted that Gender has a significant impact on creditworthiness with another few variables. The argument was that males are financially strong than females. Hence the paying ability of male clients is higher than female clients. This has been proven by Lin Li and Zhong (2012) and Peussa (2016) as well. Hence the 1st hypothesis can be developed as:

H1: The gender of the client has a significant impact on creditworthiness.

The age of the client has a significant influence on their loan status. Once clients are reaching old age, the possibility of paying installments is gradually decreasing (Samreen et al., 2013). This negative relationship between the loan status and the age of the client has been proven by Hendriadi et al. (2018) as well. However, Achsan et al. (2022) have put an opposite argument where the young tend to have a higher probability of non-performing loans than the old based on a study undertaken among Indonesian credit card holders. The condition is in line with Dong et al. (2010), Kiarie et al. (2015), Huang (2018), Kim et al. (2018), Li et al. (2019), and Obare (2019). Based on the results given by the majority of the studies, the second hypothesis is developed as:

H2: The age of the client has a significant positive impact on creditworthiness.

Rizyamesa and Rahadi (2020) have explored that five major aspects should be considered when assessing a borrower's credit risk quality. The five major aspects were based on the credit concept's 5 C's, which are character, capacity, capital, condition, and collateral. In terms of the client’s character, they have specifically identified that clients who have married have a higher payment ability than those who are single. The same type of conclusion has been raised in the studies undertaken by Samreen et al. (2013) as well. Hence based on the empirical view, the third hypothesis is developed as:

H3: Marital Status of the client has a significant positive impact on creditworthiness.

The monthly income of clients influences their ability to pay loans (Rizyamesa & Rahadi, 2020). Clients who are generating a monthly income are financially secure. However, based on their level of spending such as family support and personal spending such as consumption, higher education and etc., the paying ability can be different. The expenditure of a consumer changes based on the country's region as well. Expenditure of individuals in the urban sector is higher than rural sector (Achsan et al., 2022). According to Chen et al. (2020) in their study of an "Overview of credit scoring", indicating that the income level of clients positively influences their debt-paying ability. Hence the hypothesis can be developed as:

H4: The income Level of the client has a significant positive impact on creditworthiness.

Hasan (2016) in his study of developing a credit scoring model in Bangladesh has examined that the number of dependents is significantly influencing the creditworthiness of retail loan borrowers. Further, Samreen et al. (2013), Agbemava et al. (2016), and Hendriadi et al. (2018) have provided low scores for the personal loan borrowers in their respective banks of study by mentioning that the probability of a customer default is higher when they have more dependents to feed. Hence the 5th hypothesis is developed as:

H5: The number of Dependents of the client has a significant negative impact on Loan Status.

Abdou et al. (2007) and Abdou and Pointon (2011) used a broad review of different statistical techniques and performance evaluation criteria to investigate how credit scoring has grown in importance and to identify the key determinants in the construction of a scoring model. Among many available, they have pointed out that occupation or the employment sector has a significant influence on clients' creditworthiness. Achsan et al. (2022) have investigated that people who are self-employed have a higher nonperforming loan probability than those who are working under employers in private and public sector organizations. Similar findings have been presented by Warnakulasuriya (2016). Hence the sixth hypothesis can be developed as

H6: The employment Sector of the client has a significant impact on creditworthiness.

Rizyamesa and Rahadi (2020) explored the variables involved in credit scorecard assessment for agricultural credit granting in Agam, Indonesia. They concluded that five major aspects should be considered when assessing a borrower's credit risk quality. The five major aspects were based on the credit concept's 5 C's, which are character, capacity, capital, condition, and collateral. As a characteristic of borrowers, they have mentioned that the level of education of the borrowers is significantly influencing their creditworthiness. Borrowers who have undergraduate and postgraduate qualifications have a lower probability of non-performing than borrowers with a low level of education (Achsan et al., 2022). Hence the 7th hypothesis can be developed as:

H7: The level of education of a client has a significant positive impact on creditworthiness.

Obare et al. (2019) used the logistic regression model to examine individual loan defaults in Kenya. The study's data was gathered from the Equity Bank of Kenya by using a random sample of 1000 loan applicants having loans sanctioned by Equity Bank of Kenya. The study concluded that the applicants' loan purpose has a significant impact on creditworthiness. Lieli and White (2010) in their study of constructing credit scoring rules have also pointed out that there is a significant relationship between loan purpose and creditworthiness. Hence the 8th Hypothesis is developed as:

H8: Loan Purpose of the client has a significant impact on creditworthiness.

The main responsibility of taking the decision on the requirement of taking a loan, the amount required, and the time taken to pay the loan are in the hands of a borrower. Hence these determinants can be considered under their own characteristics though they are commonly defined as loan variables. Samreen et al. (2013) in their study have concluded that the higher the loan amount and the tenure, the higher the risk of default. The finding is in line with Rizyamesa and Rahadi (2020) and Richard and Sevias (2022) as well. Hence the ninth and the tenth hypothesis can be developed as:

H9: The loan amount of the client has a significant negative impact on creditworthiness.

H10: The loan term of the client has a significant negative impact on creditworthiness.

The creditworthiness of the client can be measured based on their prevailing performance and the risk of defaulting. If the loan payment is delayed by at least 90 days, the client is in default (Hasan, 2016). According to the new Basel II Capital Adequacy, default is defined as 90 days delinquent. This is defined by Siddiqui (2006). Kanwar (2005) defined credit risk as the risk that arises when the borrower either is unwilling to repay the loan or he is not able to repay the loan granted which results in economic loss to the bank.

III. Research Methodology

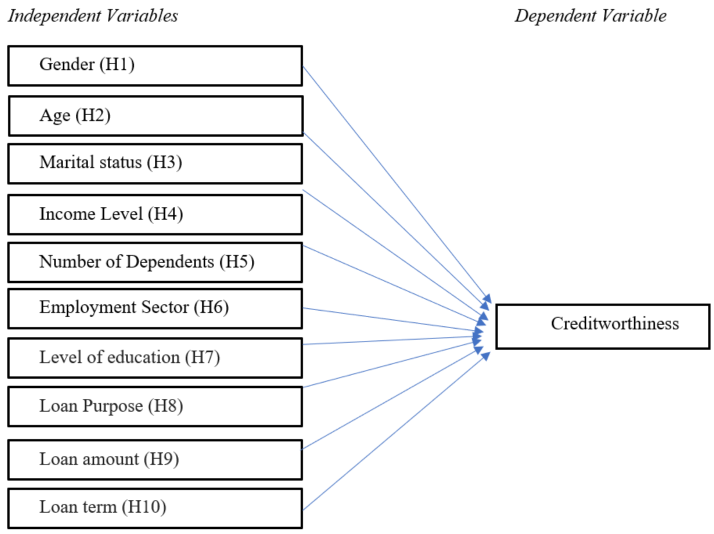
The study performs a quantitative analysis that explores the influence of the client and the loan-related predictors on the creditworthiness of the clients.

Population, Sampling Techniques, Data Collection & Data collection Method

The population of this study was the personal loan borrowers of a leading public bank in Sri Lanka. As per the annual reports released in 2020, the bank disclosed that a higher percentage (26%) of the customers reside in the western province and the Gampaha district was prioritized. After having discussions with the branch managers in the main branches, the researchers selected the major four branches near Gampaha as the client's information was not in the public domain. The sample size consisted of 130 personal loan borrowers and the data were collected under the convenience sampling technique. Performing customers were those who have finished or doing their repayment on time and default customers were those who have neither finished their payment nor payments beyond the contract expiry period. Data were collected over the sample period of 2014 to 2020 based on the borrower information given by the managers of those four main branches.

According to the comprehensive literature review conducted by the researcher, with reference to the most accepted models identified, a conceptual framework has been developed. The client's gender, age, marital status, income level, number of dependents, employment sector, level of education, loan purpose, loan amount, and the terms in months have been identified as key independent variables that would have a clear impact on creditworthiness.

Figure 1. Conceptual Framework



Source: Author Compiled

Measurement and the operationalization of variables

Table 1. Measurement and operationalization of variables

Variables	Measurement	Prior literature	Symbols
Loan status/ creditworthiness (Dependent variable)	1: performing customer if the repayments are done properly 0: defaulted customer, if delayed payment is > 90 $days$	Hasan (2016), Siddiqui (2016)	LS
Gender	Dummy variable, "0" for females and "1" for male	Samreen et al. (2013), Obare (2019)	GEN
Age	The difference between clients' date of birth and years of the study period	Obare (2019), De Silva and Weerakoon Banda (2022)	AGE
Marital status	Dummy variable, "0" for single and "1" for married	Samreen et al. (2013)	MS
Income level	Rupee value of the monthly income	Hendriadi et al. (2018), Obare (2019)	INC
Number of dependents	Total number of dependents	Samreen et al. (2013), Rizyamesa and Rahadi (2020)	ND
Employment sector	Categorical variable EMP1- "1" If the respondent is self-employed and 0 otherwise. EMP2- "1" If the respondent is working in the private sector and "0" otherwise. EMP3- "1" If the respondent working in the public sector and "0" otherwise.	Rizyamesa and Rahadi (2020), Achsan et al. (2022)	EMP
Level of education	Categorical variable EDU1 - "1" If the respondent has completed up to O/Ls and "0" otherwise.	Rizyamesa and Rahadi (2020), Achsan et al. (2022)	EDU

	EDU 2 - "1" If the respondent has completed up to A/Ls and "0" otherwise.		
	EDU 3 - "1" If the respondent is a graduate and "0" otherwise.		
	EDU 4 - "1" If the respondent has a postgraduate diploma/ degree/ above, and "0" otherwise.		
Loan purpose	Dummy variable, "1" if the loan has been taken for consumption and "0" if the loan has been taken for an investment	Lieli and White (2010)	LP
Terms in months	Number of months to maturity of the loan	Obare (2019), Richard and Sevias (2022)	LT
Loan amount	The rupee value of the loan	Lieli and White (2010), Obare (2019), Richard and Sevias (2022)	LA

Model specification

The use of logistic (Logit) in credit scoring is well-established in the literature which also shows that logistic regression is usually very successful in determining low and high-risk loans (Charitou et al., 2004; Hand & Henley, 1997). Hence the following model was applied to test the hypotheses.

$$\boldsymbol{LS}it = \boldsymbol{\beta 0}it + \boldsymbol{\beta 1}\,\boldsymbol{GEN}it + \boldsymbol{\beta 2}\,\boldsymbol{AGE}it + \boldsymbol{\beta 3}\,\boldsymbol{MS}it + \boldsymbol{\beta 4}\,\boldsymbol{INC}it + \boldsymbol{\beta 5}\,\boldsymbol{ND}it + \boldsymbol{\beta 6}\,\boldsymbol{EMP}it + \boldsymbol{\beta 7}\,\boldsymbol{EDU}it + \boldsymbol{\beta 8 LP}it + \boldsymbol{\beta 9 LT}it + \boldsymbol{\beta 10 LA}it + \boldsymbol{\varepsilon i}\,it$$

IV. Findings and Discussion

Descriptive Statistics

According to the personal characteristics of the respondents (in Table 2), among 130 loan applicants, 90 are male and 40 are female. Most of the loan applicants are married (104). Further, most of the respondents have two dependents. More than 80% of the respondents work in the public castor. 42% of the respondents have completed their education up to the Advanced level, while 35% are graduates. 6% of the respondents have postgraduate qualifications as well. In terms of the loan purpose, most of the respondents (82%) have taken loans for consumption purposes. The researchers have identified consumption purposes as wedding ceremonies, building his or her own house, buying a vehicle for own use, house repair, and buying furniture. Least respondents have taken loans for investment purposes such as for starting and upgrading their own businesses, education, and investment in properties. In terms of the characteristic of the dependent variable, 28% of the respondents are categorized as default and 72% are performing.

Table 2. Characteristics of the respondents

	Variable	Frequency Table Category	Frequency	Percentage (%)
1	Gender	Male	90	69
		Female	40	31
2	Marital Status	Single	26	20
		Marie	104	80
3	No. of Dependents	None	25	19
		One	16	12
		Two	42	32
		Three	35	26
		Four	12	9
3	Employment Sector	Self Employed	18	13
		Private	32	25
		Government	80	62
		Up to O/Ls	22	17
4	Level of education	Up to A/Ls	54	42
		Graduate	46	35
		Postgraduate Diploma and above	8	6
5	Purpose	Investment	13	10
		Consumption	6	5
6	Loan status	Perform	93	72
		Default	37	28

Source: Primary data

Descriptive statistics describe the basic features of variables in the sample. Especially the mean, minimum, maximum, standard error and skewness values of all the dependent and independent variables including continuous variables are included in Table 03. Descriptive statistics are shown based on 130 observations.

Table 3. Descriptive statistics

Variable	Minimum	Maximum	Mean	Std. Deviation	Skewness Statistic	Skewness Standard error
Loan status	0.00	1.00	0.72	0.45	-0.97	0.21
Gender	0.00	1.00	0.69	0.46	-0.84	0.21
Age	21.00	66.00	39.98	9.53	0.11	0.21
Marital status	0.00	1.00	0.80	0.40	-1.52	0.21
Monthly income	22,000.00	184,000.00	51,200.00	25,000.00	2.45	0.21
No. of Dependents	0.00	4.00	1.95	1.24	-0.22	0.21
Employment sector	1.00	3.00	2.48	0.73	-1.02	0.21
Level of Education	1.00	4.00	2.31	0.82	0.05	0.21
Loan purpose	0.00	1.00	0.82	0.38	-1.71	0.21
Loan term	24.00	180.00	73.85	26.58	1.28	0.21
Loan amount	100,000.00	2,000,000.00	775,615.38	388,806.07	1.20	0.21

Source: Primary data.

Table 3 depicts the mean value of loan status towards 0.62, which nears 01, indicating that the value is more towards the performing category. The mean value of the gender is 0.69, indicating that a respondent on average is a male.

The average age of a respondent is 40 years. The mean value of the marital status is 0.8, depicting that it is more towards the married category. The average monthly income of a respondent is Rs. 51,200.

The mean value of 1.95, under the variable of the number of dependents, depicts that respondents have nearly 2 dependents. The employment sector has three categories. 1, if the respondent is self-employed. 2, if the respondent works in the private sector and 3, if the respondent works in the public sector.

The mean value of 2.48 means that a respondent on average works in the public sector. As mentioned in Table 01, measurement and operationalization of variables, the level of education has 04 categories.

The mean value of 2.31 depicts that on average, a respondent has completed up to the Advanced level examination. The mean value of the loan purpose is 0.82, depicting that on average, a respondent has taken a loan for consumption purposes. The average loan amount that a respondent has taken is Rs. 775, 615. 38.

The skewness values of all the variables except monthly income range from -2 to +2 interpreting that the majority of the variables are normally distributed. However, that condition is not influenced by a logistic regression that the researchers have conducted to test the impact of the variables on creditworthiness.

Correlation

The significance of the correlation between the variables was assessed at the 5% significance level and detailed results of the analysis are reported in Table 4. The table shows that the monthly income of the respondents is significant at 5% and negatively correlated with loan status. The employment sector is significant at 5% and it is positively correlated with loan status. Further, the education level and the loan purpose variables are significant and positively correlated.

Table 4. Correlation analysis

	Loan status	Gender	Age	Marital status	Monthly income	No. of Dependents	Employment sector	Level of Education	Loan purpose	Loan term	Loan amount
Loan status	1										
Gender	-0.162	1									
Age	0.161	0.001	1								
Marital status	0.026	-0.125	.497**	1							
Monthly income	-.311**	0.109	0.010	0.137	1						
No. of Dependents	0.028	-.204*	.368**	.756**	0.076	1					
Employment sector	.509**	-0.136	-0.015	-0.069	-.362**	0.02	1				
Education	.506**	-.318**	0.110	-0.023	-0.008	-0.014	.464**	1			
Loan Purpose	.288**	-0.003	-0.022	-0.030	-.379**	0.110	.499**	.247**	1		
Loan term	-0.041	0.062	-0.103	0.113	-0.145	0.167	0.094	-0.03	.242**	1	
Loan amount	-0.100	0.016	-0.147	0.096	.351**	0.091	0.087	0.054	-0.084	.458**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Results of the Logit Model

In the study, the dependent variable "creditworthiness/ loan status" is a categorical variable. Hence a logistics regression was conducted to analyze the impact of independent variables on the dependent variable. VIF test statics below 5 indicated that there is no multicollinearity issue and strongly influential outliers were already eliminated by the researcher. The estimation results of the logistic regression model consist of 10 independent variables. The Omnibus test of the model coefficient shows Chi-square statistics with a significant level of less than 5%, meaning there is a significant impact of the independent variables simultaneously on the dependent variable.

Table 5. Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	80.26	12	.000
	Block	80.26	12	.000
	Model	80.26	12	.000

The Cox & Snell R Square and Nagelkerke R square of the regression model summary in Table 6, indicates that between 39.1% and 56.1% of the dependent variable is explained by the independent variables.

Table 6. Regression Model Summary

-2 Log-likelihood	Cox & Snell R Square	Nagelkerke R Square
91.350[a]	.391	.561

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

The Hosmer and Lemeshow test in Table 7 indicates a significant value that is greater than 5% mentioning that the overall model is fitted.

Table 7. Hosmer and Lemeshow test results

Step	Chi-square	Df	Df
1	6.310	8	.613

The independent variables that partially effect on creditworthiness can be seen from Wald test results with a significantly less than 0.05. Based on the Wald test results in Table 8, the age, monthly income, number of dependents, level of education, and loan term of the respondents have a significant impact on their creditworthiness.

Table 8. Logistic regression estimation results

Variable	Coefficient	Standard Error	Wald Test Values	Sig.	Exp(B)
Gender (Male)	-.008	.766	.000	.992	.992
Age	.177**	.040	1.820	.044	1.055
Marital status (Married)	1.006	1.101	.835	.361	2.735
Monthly Income	2.105*	1.167	3.256	.071	.122
No. of Dependents	-.148*	.364	.164	.085	.863
Employment (Base group: Self-employed)					
Private sector employee	.365	1.268	.083	.774	1.440
Public sector employee	1.693	1.260	1.805	.179	5.435
Education (Base group: Education is up to O/Ls)					
Education up to A/Ls	1.941**	.796	5.940	.015	6.965
Graduate	3.771**	.998	14.274	.000	43.408
Postgraduate Diploma and above	3.858*	1.881	3.188	.074	28.741
Loan Purpose	.425	.947	.201	.654	1.529
Loan term	-.017*	.013	1.718	.090	.983
Loan amount	.185	.680	.074	.786	1.203
Constant	16.438	12.869	1.632	.201	13773118.095

Note: *Coefficients significant at 90% confidence level, **coefficients significant at 95% confidence level

The gender of the respondent does not have a significant impact on creditworthiness. Hence H1; The gender of the client has a significant impact on creditworthiness is rejected. However, the negative coefficient depicts that males are poor in paying loans than females. The results received in the study are a bit contradictory to Samreen et al. (2013) who have concluded that male borrowers are more creditworthy than female borrowers as they are financially secure. However, Kiari et al. (2015) and Lieli and White (2010) have found an insignificant impact of gender on creditworthiness. They have even mentioned that gender is used as a scorecard component with less weight.

The age of the respondent has a significant positive impact on creditworthiness with a coefficient of 0.177. Hence H2; The age of the client has a significant positive impact on creditworthiness is accepted. This condition is in line with Obare (2019), and Achsan et al. (2022) who have justified that with age maturity people become financially stable.

Based on the findings in Table 8, marital status shows a positive coefficient, depicting that married customers are more creditworthy. However, the impact is not statistically significant. Hence H3; The marital status of the client has a significant impact on creditworthiness is rejected. Marital status can matter if it has an effect on the responsibility, reliability, or maturity of borrowers. The support given by the partner can have a positive impact on the ability to pay off loans (Kleimeier, 2007). Samreen et al. (2013) have also given a higher score for married respondents when designing a credit scoring model. However, Achsan et al. (2022) have indicated that single customers are more creditworthy than married customers as they have fewer financial responsibilities in terms of feeding the family.

The monthly income of the respondents is marginally significant under a 90% confidence level and has a positive coefficient of 2.105. Hence H4; The monthly income of the client has a significant positive impact on creditworthiness is accepted. The result is in line with Abdou et al. (2007) and Jacobson and Roszbach (2003). However, disposable income is preferred when assessing creditworthiness over monthly income. Further, creditworthiness cannot be measured by income level correctly unless the loan amount is determined based on income. A person with a higher income can go with a higher loan amount and a person with a lower income can go with a lower loan amount (Dinh & Kleimeier, 2007).

The number of dependents also has a statistically significant association with loan status. The negative coefficient of -0.148 indicates that a high number of dependents leads to reduce payment ability of borrowers. Hence H5; The number of dependents of the client has a significant negative impact on creditworthiness is accepted. The number of dependents represents the number of people that the borrower has to support, mostly the number of children. As the number of dependents increases, so does the pressure on the borrower's income due to higher expenses such as school fees (Dinh & Kleimeier, 2007). Marital status and the number of dependents can also have a significant interrelationship. Those who are married and have more dependents may be less creditworthy than those married with fewer dependents.

Based on the results of Table 8, The employment sector does not show a significant impact on creditworthiness. Hence H6; The employment sector of the client has a significant impact on creditworthiness is rejected. However, a higher positive coefficient in the public sector indicates that public sector employees have low credit risk. Achsan et al. (2022) have mentioned that self-employed individuals have a higher credit risk than non-self-employed. It implies that the risk of employment affects creditworthiness. Samreen et al. (2013) in their study of developing a credit scoring model in Commercial Banks in Pakistan have given a higher score for salaried employees than self-employed.

The results of Table 8 depict that with a higher level of education, borrowers are capable of paying the loans. Hence H7; The level of education of the client has a significant positive impact on creditworthiness. Samreen et al. (2013), Lv et al. (2017), and Achsan et al. (2022) have concluded their results in line with the results of this study. However, Dinh and Kleimeier (2007) have mentioned that default frequencies of the borrowers do not decline with increasing education among women in Vietnam.

The logistic regression results do not provide a significant link between loan status and the loan purpose of the clients. Hence H8; The loan purpose of the client has a significant impact on creditworthiness is rejected. This finding contradicts the findings of Lieli and White (2010) and Samreen et al. (2013) who found a significant relationship between loan purpose and loan status.

The logistic regression does not result in a significant impact of the loan amount on the creditworthiness of borrowers. Hence H9; The loan amount of the client has a significant negative impact on creditworthiness is rejected. The results are contradictory with the findings of Stiglitz and Agarwal et al. (2009), and Lv et al. (2017), who reported a negative and significant association between loan quantity and loan status.

Further, the logistic regression shows a negative significant impact of the loan term on the creditworthiness of borrowers. Hence H10; The loan term of the client has a significant negative impact on creditworthiness is accepted. The default risk of a loan with long tenure is expected to be high (Hendriadi et al., 2018).

Default Observed and Predicted

The classification table shows how effectively the accuracy of the model can be predicted which in this case is the probability that a borrower defaults in loan repayment. Overall, 85.4% of cases were accurately classified by the proposed model. The model exhibits a good sensitivity since among those customers who perform over default, 95.7% were correctly predicted as performing clients.

Table 9. Classification Table

Observed			Predicted: Loan status — Default	Predicted: Loan status — Performing	Percentage Correct
Step 1	Loan status	Default	22	15	59.5
		Performing	4	89	95.7
	Overall Percentage				85.4

V. Conclusion

As per the research outcome, the determinants such as age, monthly income, number of dependents, level of education, and the loan term of the borrowers had a significant influence on their creditworthiness. Increasing nonperformance customers is a significant issue in the financial sector of Sri Lanka. As a solution, these institutions in the financial sector are trying to gather knowledge on the development of credit scoring models as credit risk is considered as one of the most harmful because bad debt would impair the profits of financial institutions. However, these models are not yet popular in Sri Lanka and the existing studies are very less. Hence to continue forward with this identified issue, in this study, the researchers have examined the characteristics affecting creditworthiness for which the financial institutions can pay attention to minimize their Non-Performance (NP) ratio and identify who are the high-risk clients and who are the low-risk clients by utilizing these findings. Hence this study will be helpful to banks and future researchers to create an effective model to assess the creditworthiness of personal loan customers. It is highly recommended for the commercial banks to pay attention to these identified characters once they may develop their own credit scoring models or can update identified significant factors as a part of their evaluation process.

As the limitations of the study, various constraints were faced in data gathering and estimation techniques throughout the investigation. Only one major bank in Sri Lanka had access to the data used for the study, raising concerns about how the conclusion can be generalized to the entire banking sector and segment. It is suggested that advanced credit scoring systems such as genetic algorithms, fuzzy discriminant analysis, and neural networks be used in future research investigations with more data to enhance accuracy. New variables can also be found that will aid in predicting the likelihood of people and organizations defaulting. Further, it is highly recommended that data from more rejected applicants by banks be collected to achieve more diverse results.

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