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Development of a Predictive Model in Mapping the Payment Trajectories of Low-income Borrowers Using Logistic Regression Analysis

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Abstract

One of the main challenges faced by low-income borrowers is the high incidence of loan default and delinquency. Consequently, there is a need to identify the factors that influence loan repayment behavior and develop a predictive model that can forecast the likelihood of default or delinquency. To address this issue, this study developed a predictive model that accurately predicts loan repayment behavior, so that the potential negative impacts on both borrowers and lenders can be mitigated, promoting financial stability and inclusive growth. This study employed a quantitative research design, specifically utilizing logistic regression analysis, to develop a predictive model for mapping the payment trajectories of the 242 low-income borrowers in Occidental Mindoro, Philippines, who were selected using stratified random sampling. The findings revealed that the developed model effectively captures the variations in low-income borrowers' payment trajectories, accurately distinguishing between making timely payments or failing to make timely payments. By understanding the demographic characteristics, income sources, and factors that influence repayment behavior, tailored financial interventions can be designed to provide affordable credit options, promote financial education, and support borrowers in making timely payments. A specific recommendation is to develop comprehensive financial education programs tailored specifically for low-income borrowers. These programs should focus on improving financial literacy, budgeting skills, and informed decision-making by addressing the knowledge gap identified among this population.

Keywords: *logistic regression analysis, low-income borrowers, payment trajectories, poverty eradication, predictive model.*

Introduction

In the Philippines, where poverty and income inequality remain significant challenges, understanding the payment trajectories of low-income borrowers is of paramount importance. With approximately 26.50% of the population living below the poverty line (World Bank, 2021), there is a pressing need to address the financial challenges faced by low-income individuals and promote their financial well-being. By developing a predictive model that accurately maps the payment trajectories of these borrowers, financial institutions can make informed decisions regarding credit risk assessment, loan pricing, and repayment terms (Cabatingan et al., 2019).

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Furthermore, the development of a predictive model for low-income borrowers aligns with the Philippine government's goal of achieving inclusive growth and reducing poverty. The government has recognized the importance of financial inclusion in poverty reduction strategies, aiming to provide access to formal financial services to the unbanked and underbanked sectors of society (Bangko Sentral ng Pilipinas, 2021). By understanding the payment behavior of low-income borrowers, policymakers can design targeted interventions, such as financial literacy programs or loan restructuring initiatives, to improve their financial management skills and increase their chances of successful loan repayment (Hoggarth et al., 2017).

Occidental Mindoro, a province in the Philippines, presents a unique context for studying the payment trajectories of low-income borrowers. The province has a predominantly agricultural economy, with many residents relying on farming as their primary source of income. The income volatility and seasonal nature of agricultural activities pose specific challenges for financial management and loan repayment among low-income borrowers in Occidental Mindoro (Montefrio & David, 2020). Therefore, developing a predictive model that accounts for these contextual factors can provide valuable insights into the payment behavior of low-income borrowers in this region.

Moreover, Occidental Mindoro has a significant presence of microfinance institutions (MFIs) that cater to the financial needs of low-income individuals. These MFIs play a vital role in providing access to credit and other financial services to underserved communities. However, they face challenges in accurately assessing credit risk and predicting repayment behavior due to limited borrower information and lack of sophisticated risk assessment tools (Valdez et al., 2018). By developing a predictive model that incorporates relevant borrower characteristics, such as demographic factors, loan attributes, and repayment history, this research can assist MFIs in improving their credit risk management practices and ultimately contribute to their financial sustainability.

One of the main challenges faced by low-income borrowers in Occidental Mindoro is the high incidence of loan default and delinquency. Limited financial resources, inadequate financial management skills, and unforeseen events, such as natural disasters or health emergencies, contribute to repayment difficulties among this vulnerable population (Javelosa, 2019). Consequently, there is a need to identify the factors that influence loan repayment behavior and develop a predictive model that can forecast the likelihood of default or delinquency.

Understanding the underlying factors that influence loan repayment behavior is crucial for designing effective risk management strategies and interventions. Previous research has identified various determinants of loan repayment behavior, such as borrower characteristics (e.g., age, education level), loan characteristics (e.g., loan amount, interest rate), and external factors (e.g., economic conditions) (Adekanye et al., 2016; Wadud et al., 2020). However, limited research has specifically focused on developing predictive models for low-income borrowers in Occidental

Mindoro using logistic regression analysis, which can provide a more nuanced understanding of the payment trajectories of this specific population.

The high incidence of loan default and delinquency among low-income borrowers in Occidental Mindoro has significant implications for both the borrowers and the financial institutions. Defaults lead to financial losses for lenders and potentially hinder their ability to provide loans to other borrowers. For borrowers, defaults can result in negative credit histories, restricted access to formal financial services, and increased vulnerability to predatory lending practices (Hermes & Lensink, 2018). By developing a predictive model that accurately predicts loan repayment behavior, the potential negative impacts on both borrowers and lenders can be mitigated, promoting financial stability and inclusive growth.

Although previous studies have examined loan repayment behavior and developed predictive models for borrowers in different contexts, there is a research gap regarding the development of such models specifically tailored for low-income borrowers in Occidental Mindoro, Philippines. By utilizing logistic regression analysis, this research sought to bridge this gap by considering the unique characteristics and challenges faced by low-income borrowers in Occidental Mindoro, providing valuable insights into their payment trajectories and enhancing the accuracy of credit risk assessment for financial institutions operating in the region.

To support this study, the theoretical framework of the study was based on the behavioral economics theory. Behavioral economics offers valuable insights into understanding individual decision-making processes and how cognitive biases and heuristics influence financial behavior (Thaler, 2016). By applying this framework, the research uncovered the psychological and behavioral factors that influence the payment trajectories of low-income borrowers. Incorporating behavioral economics into the development of the predictive model can improve its accuracy and enhance its practical implications for financial institutions and policymakers in Occidental Mindoro.

Materials and Method

This study employed a quantitative research design, specifically utilizing logistic regression analysis, to develop a predictive model for mapping the payment trajectories of low-income borrowers. Logistic regression allows for the examination of the relationship between a set of predictor variables and a binary outcome variable, which in this case is the payment behavior of borrowers. By analyzing the historical payment data of low-income borrowers, the study aims to identify significant predictors and create a model that can forecast future payment trajectories.

Data from each microfinance institution in Occidental Mindoro, Philippines, revealed that there was a total of 1,628 low-income borrowers in the province. The sample size was calculated using the Raosoft formula as follows:

$$x = Z(^{c}/_{100})^2 r(100-r),\ n = {}^{Nx}/_{((N-1)E^2 + x)},\ \text{and}\ E = \mathrm{Sqrt}[^{(N-n)x}/_{n(N-1)}],$$

With N equaling the population size, r equaling the proportion of replies the researchers are interested in, and $Z(c/100)$ equaling the confidence level c's critical value. Consequently, the study required a minimum sample size of 311 low-income borrowers. However, to be considered in the sample selection, the low-income borrowers had to meet the following criteria:

Inclusion Criteria:

1. The individual must have been a borrower for at least a year;
2. The individual should have encountered being in arrears with payments; and
3. The individual must have been operating a small business or microenterprise for at least three years.

Exclusion Criteria:

1. Low-income borrowers who are not situated in the mainland province of Occidental Mindoro, Philippines, are not considered in the study; and
2. Borrowers who have loans other than microfinance loans are excluded.

Withdrawal Criteria:

1. If the respondents in the study experience any adverse effects as a result of their participation, they may be withdrawn from the study immediately. Adverse effects could include physical harm, emotional distress, or other negative consequences.
2. If the respondents provide false or misleading information during the study, they may be withdrawn from the study. This is to ensure the validity and reliability of the data collected.
3. If the respondents decide to withdraw their participation from the study, they will be allowed to do so without any penalty or consequences.
4. If the respondents become unreachable or unresponsive despite repeated attempts to contact them, they may be withdrawn from the study. This is to ensure that data collection is completed within the designated time frame.

By considering these criteria, only 242 low-income borrowers were included in the study among the 311 low-income borrowers in Occidental Mindoro, Philippines. Since this study only had 32 registered microfinance institutions as its respondents, the complete enumeration or census procedure was used. On the other hand, stratified random sampling was used in selecting the 242 low-income borrowers in Occidental Mindoro, Philippines. In this study, the strata that were used were the types of microfinance institutions which included private sector (rural banks), cooperative, and non-governmental organizations. Table 1 reveals that the total sample size intended for the private sector (rural banks), cooperative, and non-governmental organizations was 106, 38, and 98, respectively.

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Table 1. Selection of sample size based on strata.

Strata	Population Size		Sample Size
	Microfinance Institutions	**Low-income Borrowers**	**Low-income Borrowers**
Private Sector (Rural Banks)	14	759	106
Cooperative	5	259	38
Non-governmental Organization	13	610	98
Total	**32**	**1,628**	**242**

A researcher-constructed survey questionnaire was utilized for data gathering in this study. Part I focused on the socio-demographic profile of low-income borrowers in Occidental Mindoro, Philippines. Part II examined the economic profile of low-income borrowers in Occidental Mindoro, Philippines.

Part III focused on the credit profile of the low-income borrowers. Part IV examined the psychological and behavioral factors that influence the payment trajectories of low-income borrowers. Pilot testing was conducted after the survey questionnaire had been accepted and tested to assess its reliability and ensure that respondents interpreted the questions in the intended manner.

For the data analysis, socio-demographic, economic, credit profiles, and psychological and behavioral factors were gathered using frequency and percentage distribution. Furthermore, logistic regression analysis was employed to analyze the factors affecting the payment trajectories of low-income borrowers in Occidental Mindoro, Philippines. Model specification* is presented in Equation 1 below:

Payment trajectories$_i$ = β_0 + β_1Age + β_2Sex + β_3Education level + β_4Marital status

+ β_5Household size + β_6Geographic location + β_7Occupation + β_8Other sources of income + β_9Total monthly household income + β_{10}Total amount of loan payable + β_{10}Credit history + β_{11}Debt burden + β_{12}Loan terms + β_{13}Financial management skills + ε_i

The dependent variable (Payment trajectories$_i$) in logit regression analysis is interpreted as "the log of the odds ratio of low-income borrower making timely payments or failing to make timely payments" and is computed as $\ln \frac{Pi}{1-Pi} = Z$ (Equation 2).

After meticulously developing and validating the questionnaire, it was administered to 242 low-income borrowers. Ethical considerations were taken into account to protect the rights and well-being of the respondents. To protect the privacy and confidentiality of research information, the study adhered to strict data protection protocols. All research data were stored securely, with access

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restricted to authorized personnel only. Personal information of respondents was de-identified to ensure anonymity, and only aggregate data were reported in the study.

Results

Socio-demographic Profile of the Low-income Borrowers

Table 2 presents the demographic distribution of low-income borrowers. Among this group, 26.03% fall within the 32-38 age range, while 55.37% are female. Additionally, 24.79% are high school undergraduates, 50.83% are married, and 29.34% belong to households with 3-4 members. Furthermore, 48.35% of the low-income borrowers are located in rural areas.

Table 2. Socio-demographic profile of low-income borrowers in Occidental Mindoro, Philippines.

Socio-demographic Profile	Frequency	Percentage
Age		
25-31 years old	44	18.18
32-38 years old	63	26.03
39-45 years old	56	23.14
46-52 years old	42	17.36
53-59 years old	37	15.29
Total	**242**	**100.00**
Sex		
Male	108	44.63
Female	134	55.37
Total	**242**	**100.00**
Education Level		
No Formal Schooling	31	12.81
Elementary Undergraduate	46	19.01
Elementary Graduate	56	23.14
High School Undergraduate	60	24.79
High School Graduate	49	20.25
Total	**242**	**100.00**
Marital Status		
Single	64	26.45
Married	123	50.83
Divorced/Separated	34	14.05
Widows/Widowers	21	8.68
Total	**242**	**100.00**
Household Size		
3-4 members	71	29.34

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5-6 members	41	16.94
7-8 members	44	18.18
9-10 members	44	18.18
11-12 members	42	17.36
Total	**242**	**100.00**
Geographic Location		
Urban	47	19.42
Suburban	78	32.23
Rural	117	48.35
Total	**242**	**100.00**

Economic Profile of the Low-income Borrowers

Table 3 reveals that the majority of low-income borrowers, comprising 18.18%, are washerwomen. Another significant source of income for them is the buy and sell/sari-sari store, which accounts for 25.21%. Additionally, 12.81% of low-income borrowers have a total household monthly income ranging from ₱13,411 to ₱14,707. Conversely, 12.81% have total loan amounts payable ranging from ₱266,998 to ₱311,330, as well as ₱355,665 to ₱400,000.

Table 3. Economic profile of low-income borrowers in Occidental Mindoro, Philippines.

Economic Profile	Frequency	Percentage
Occupation		
Fisherman	35	14.46
Vendor	35	14.46
Sari-sari Store Owner	31	12.81
Employee/Businessman/Professional	27	11.16
Farmer	36	14.88
Washerwoman	44	18.18
Housewife	34	14.05
Total	**242**	**100.00**
Other Sources of Income		
Buy and sell/Sari-sari Store	61	25.21
Farming/Farm Laborer/Fishing	39	16.12
Business Owner/Manager	43	17.77
Salary from Relatives	48	19.83
None	51	21.07
Total	**242**	**100.00**
Total Monthly Household Income		
₱9,520-₱10,816	26	10.74

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₱10,817-₱12,113	23	9.50
₱12,114-₱13,410	34	14.05
₱13,411-₱14,707	31	12.81
₱14,708-₱16,004	25	10.33
₱16,005-₱17,301	30	12.40
₱17,302-₱18,598	22	9.09
₱18,599-₱19,895	21	8.68
₱19,896-₱21,194	30	12.40
Total	**242**	**100.00**
Total Amount of Loan Payable		
₱1,000-₱45,332	30	12.40
₱45,333-₱89,665	27	11.16
₱89,666-₱133,998	23	9.50
₱133,999-₱178,331	27	11.16
₱178,332-₱222,664	28	11.57
₱222,665-₱266,997	20	8.26
₱266,998-₱311,330	31	12.81
₱311,331-₱355,663	25	10.33
₱355,665-₱400,000	31	12.81
Total	**242**	**100.00**

Credit Profile of the Low-income Borrowers

Table 4 reveals that 29.33% of low-income borrowers have a poor credit history, characterized by instances of delinquency or default. Additionally, 68.18% of this group fails to make timely payments, while 28.93% experience an overwhelming debt burden and encounter significant difficulties in repayment. On a positive note, 23.14% benefit from low-interest loans with favorable repayment terms. However, 25.20% of the respondents possess minimal knowledge of financial management and consequently struggle to make informed decisions.

Table 4. Credit profile of low-income borrowers in Occidental Mindoro, Philippines.

Credit Profile	Frequency	Percentage
Credit History		
No previous credit history	48	19.83
Limited credit history with a few accounts	63	26.03
Poor credit history with instances of delinquency or default	71	29.33
Fair credit history with occasional late payments	44	18.18
Good credit history with consistent on-time payments	16	6.61

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Total	**242**	**100.00**
Payment Trajectories		
Makes timely payments	77	31.82
Fails to make timely payments	165	68.18
Total	**242**	**100.00**
Debt Burden		
Minimal debt burden with few outstanding loans or debts	23	9.50
Moderate debt burden with manageable monthly payments	39	16.12
High debt burden with difficulties in meeting monthly obligations	51	21.07
Overwhelming debt burden with significant difficulties in repayment	70	28.93
Severe debt burden with multiple accounts in collections or bankruptcy	59	24.38
Total	**242**	**100.00**
Loan Terms		
Low-interest loan with favorable repayment terms	56	23.14
Moderate interest rates with standard repayment periods	54	22.31
High-interest loans with shorter repayment periods	51	21.07
Predatory loans with exorbitant interest rates and unfavorable terms	41	16.94
Irregular or unregulated loans with exploitative conditions	40	16.53
Total	**242**	**100.00**
Financial Management Skills		
Strong financial literacy and effective money management skills	36	14.88
Adequate understanding of personal finance but occasional budgeting challenges	44	18.18
Limited financial literacy with difficulties in budgeting and planning	48	19.83
Minimal knowledge of financial management and struggles to make informed decisions	61	25.20
Lack of basic financial literacy and poor management skills	53	21.90

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Total	**242**	**100.00**

Factors Affecting the Payment Trajectories of the Low-income Borrowers

Table 5 displays the outcomes of the logistic regression analysis as outlined in Equation 1. The statistical significance of the model, in terms of estimating payment trajectories for low-income borrowers, is remarkably high with a probability of Prob>chi^2 = 0.0001 and a pseudo R^2 value of 0.2714. These results indicate that the model effectively captures the variations in low-income borrowers' payment trajectories, accurately distinguishing between making timely payments or failing to make timely payments.

The specified model can be reconfigured based on the outcomes derived from the logistic regression analysis:

Payment trajectories$_i$ = 17.22 + 0.020Age + 1.471Sex + 15.623Education level +

0.421**Marital status + 0.442***Household size + 2.046Geographic location + 0.044**Occupation + 1.988*Other sources of income + 0.213**Total monthly household income + 1.264***Total amount of loan payable + 0.025**Credit history + 0.818*Debt burden + 0.021***Loan terms + 0.001*Financial management skills

The identified independent variables that theoretically impact the payment trajectories of low-income borrowers demonstrate significant predictive power at different levels. Household size, total amount of loan payable, and loan terms emerge as highly significant predictors at the 1% level. Furthermore, marital status, occupation, total monthly household income, and credit history serve as indicators at the 5% level. Predictors at the 10% level include other sources of income, debt burden, and financial management skills.

Table 5. Factors affecting payment trajectories of low-income borrowers in Occidental Mindoro, Philippines.

Variables	Coefficient	Std. Error
Age	0.020	0.053
Sex	1.471	0.246
Education Level	15.623	124.387
Marital Status	-0.421**	1.432
Household Size	-0.442***	0.131
Geographic Location	2.046	0.646
Occupation	0.044**	0.229
Other Sources of Income	1.988*	0.820
Total Monthly Household Income	0.213**	0.519
Total Amount of Loan Payable	-1.264***	0.612
Credit History	-0.025**	0.804
Debt Burden	-0.818*	0.008

Loan Terms	0.021***	0.027
Financial Management Skills	0.001*	0.122

Legend: *** - significant at 1% level; ** - significant at 5% level; *-significant at 10%

Marginal Effects of Significant Variables After Logistic Regression Analysis

Interpreting the coefficients of the significant variables reveals the following effects: (i) If the low-income borrower is married, the log of the odds ratio for making timely payments decreases by 0.421. (ii) If the household size increases by 1 member, the log of the odds ratio for making timely payments decreases by 0.442. (iii) If the low-income borrower has an occupation, the log of the odds ratio for making timely payments increases by 0.044. (iv) If the low-income borrower has other sources of income, the log of the odds ratio for making timely payments increases by 1.988. (v) If the total monthly household income increases by PhP1, the log of the odds ratio for making timely payments increases by 0.213. (vi) If the total amount of loan payable increases by PhP1, the log of the odds ratio for making timely payments decreases by 1.264. (vii) If the low-income borrower has a poor credit history with instances of delinquency or default, the log of the odds ratio for making timely payments decreases by 0.025. (viii) If the low-income borrower has an overwhelming debt burden with significant difficulties in repayment, the log of the odds ratio for making timely payments decreases by 0.818. (ix) If the low-income borrower has a low-interest loan with favorable repayment terms, the log of the odds ratio for making timely payments increases by 0.021. (x) If the low-income borrower has minimal knowledge of financial management and struggles to make informed decisions, the log of the odds ratio for making timely payments decreases by 0.001.

Table 6 presents the marginal effects of variables obtained from the logistic regression analysis. These effects reveal the impact of changes in significant factors on the likelihood of timely payments by low-income borrowers. For instance, considering loan terms as a predictor variable, a marginal effect of 0.0002 implies that if low-income borrowers have access to low-interest loans with favorable repayment terms, their probability of making timely payments increases by 0.02%.

Table 6. Marginal effects of significant variables after logistic regression analysis.

Variables	Marginal Effects
Marital Status	-0.04%
Household Size	-0.04%
Occupation	0.04%
Other Sources of Income	0.01%
Total Monthly Household Income	0.02%
Total Amount of Loan Payable	-0.01%
Credit History	-0.02%

Debt Burden	-0.08%
Loan Terms	0.02%
Financial Management Skills	0.10%

Discussion

The demographic distribution of low-income borrowers reveals several key characteristics that are important in understanding their financial situation. Firstly, a significant portion (26.03%) of low-income borrowers falls within the 32-38 age range, indicating that a considerable number of individuals in their early adulthood are facing financial challenges. This finding aligns with the notion that young adults often experience financial instability as they navigate their careers and establish financial independence (Smith, 2018). Furthermore, the fact that 55.37% of low-income borrowers are female highlights the gender disparity in economic opportunities and financial access, as women tend to face more significant barriers to financial inclusion (Kabeer, 2015). These demographic characteristics provide insights into the specific target population that requires tailored financial assistance programs.

Another crucial aspect of the demographic distribution is the representation of various household and marital statuses. Approximately 24.79% of low-income borrowers are high school undergraduates, suggesting that education level is an important factor in their financial situation. Lower educational attainment can limit employment prospects and earning potential, contributing to financial vulnerability (Haveman & Wilson, 2018). Additionally, the finding that 50.83% of low-income borrowers are married indicates the potential interplay between household dynamics and financial struggles. Marriage and family responsibilities can significantly impact financial decisions and resource allocation (Browning & Chiappori, 2014). Moreover, 29.34% of low-income borrowers belong to households with 3-4 members, suggesting that family size plays a role in financial constraints. Larger households may face higher expenses and greater financial strain, leading to a higher likelihood of seeking financial assistance (Glynn & Maclean, 2019). Lastly, the fact that 48.35% of low-income borrowers are located in rural areas highlights the significance of geographic context in understanding financial challenges. Rural communities often face unique economic circumstances, limited job opportunities, and reduced access to financial services (Cromartie & Nelson, 2016).

The sources of income for low-income borrowers provide insights into their economic activities and financial diversity. Among the respondents, 18.18% work as washerwomen, indicating that this occupation plays a substantial role in their income generation. This finding aligns with the reality of informal and low-wage work being prevalent among low-income individuals (Deleuze, 2016). Additionally, the buy and sell/sari-sari store represents a significant source of income for 25.21% of low-income borrowers. These small retail businesses are common in many low-income communities and contribute to local economic activity (Saulon, 2021). Understanding the diverse sources of income can inform the design of financial interventions that address the specific needs and challenges of these income-generating activities.

The statistical analysis reveals important patterns and predictors related to low-income borrowers' payment trajectories. A notable finding is that 29.33% of low-income borrowers have a poor credit history, characterized by delinquency or default. This indicates a history of financial difficulties and potentially limited access to traditional credit sources (Shin, 2016). Moreover, the high percentage (68.18%) of borrowers who fail to make timely payments underscores the challenges they face in meeting their financial obligations. Financial instability and irregular cash flows can contribute to payment delinquency (Birkenmaier et al., 2018). Additionally, the finding that 23.14% benefit from low-interest loans with favorable repayment terms suggests the importance of affordable and accessible credit options in supporting low-income borrowers. However, it is concerning that 25.20% of respondents possess minimal knowledge of financial management, as this lack of financial literacy can hinder their ability to make informed decisions and manage their finances effectively (Lusardi & Mitchell, 2014). These findings emphasize the importance of financial education and support services in improving the financial well-being of low-income borrowers.

The logistic regression analysis provides insights into the predictive power of independent variables in estimating payment trajectories for low-income borrowers. The results indicate that certain factors significantly impact the likelihood of making timely payments. Variables such as household size, total amount of loan payable, loan terms, marital status, occupation, total monthly household income, credit history, other sources of income, debt burden, and financial management skills are all identified as predictors with varying levels of significance. These findings align with existing literature that highlights the multifaceted nature of financial behavior and the interplay of various factors in shaping individuals' repayment patterns (Bruhn et al., 2019). By quantifying the effects of these variables, the analysis provides a deeper understanding of their relative importance in influencing timely payments among low-income borrowers.

The marginal effects derived from the logistic regression analysis further elucidate the impact of changes in significant factors on the likelihood of timely payments by low-income borrowers. For instance, the marginal effect of 0.0002 for loan terms indicates that accessing low-interest loans with favorable repayment terms can increase the probability of making timely payments by 0.02%. This finding suggests that providing affordable credit options can have a positive effect on borrowers' repayment behavior and overall financial stability. The marginal effects provide policymakers and financial institutions with actionable insights to develop targeted interventions and policies aimed at improving the repayment outcomes of low-income borrowers.

Conclusions

The analysis of low-income borrowers' demographic distribution, income sources, credit history, and predictive factors provides valuable insights for policymakers, financial institutions, and stakeholders working towards improving the financial well-being of this population. The findings highlight the importance of addressing the unique challenges faced by low-income borrowers, including limited access to credit, financial instability, and a lack of financial literacy. By understanding the demographic characteristics, income sources, and factors that influence repayment behavior, tailored financial interventions can be designed to provide affordable credit options, promote financial education, and support borrowers in making timely payments. These efforts can contribute to enhancing financial inclusion and empowering low-income borrowers to achieve greater financial stability and resilience.

Based on the findings and insights from the analysis, a specific recommendation is to develop comprehensive financial education programs tailored specifically for low-income borrowers. These programs should focus on improving financial literacy, budgeting skills, and informed decision-making by addressing the knowledge gap identified among this population. By providing accessible and relevant financial education modules, incorporating strategies to address income diversification and entrepreneurship, and establishing partnerships with financial institutions and non-profit organizations, policymakers and stakeholders can empower low-income borrowers with the necessary skills and knowledge to navigate their financial challenges, improve their repayment behavior, and enhance their overall financial well-being.

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