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Binary logistic regression modelling of tertiary institution students' loan approval

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ABSTRACT

The high cost of tuition and other educational resources makes it difficult for students in Nigeria to access postsecondary education, placing a financial strain on both the students and their parents. Due to difficulties brought by the high cost of tuition, the Nigerian government established the Student Loan Program to assist students who are unable to pay for tuition and other educational expenses. Despite the Nigerian government's efforts, the country's student loan approval and uptake rates are still shockingly low, which raises a number of concerns about the factors compromising the loans' ability to effectively address educational disparities. This study, grounded on the Human Capital Theory employs a binary logistics regression to model the loan approval rate for Nigerian students enrolled in higher institutions. Data utilized in this study was sourced from the Nigeria Education Loan Fund (NELFUND) online database. This study found that under graduates and students with high Credit Information Bureau (India) Limited (CIBIL) score were more likely to get a student's loan request approved than graduated students with low CIBIL scores. The study also revealed that the students' income per annum, loan amount and bank asset value had a positive and insignificant influence on students' loan approval. Recommendation from the study's findings was that NELFUND should take into account the knowledge gathered to improve their loan approval procedure by concentrating on the applicant's credit score and modifying the educational status requirements to attain a more precise and equitable loan distribution.

Keywords: students' loan scheme, economic constraints, logistic regression, loan approval, NELFUND

INTRODUCTION

Everyone agrees that education is essential to empowering people for both national and personal growth (Olanipekun et al., 2024; Victor, 2024; World Bank, 2021). Nigeria, a country with more than 270 universities, views higher education as a means of gaining the information and abilities necessary to promote innovation, which in turn can result in the economic progress of the country. However, the high cost of tuition, books, housing, food, and other educational resources makes it difficult for students in Nigeria to attend postsecondary education, placing a financial strain on both the students and their parents or guardians, if applicable. Many students, especially those from low-income households, are unable to pursue higher

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education because of this financial load. Since the high expense of education is a major economic issue in Nigeria, many students from low-income families find it difficult to obtain high-quality education. Student loans are becoming a crucial tool for bridging the gap between parents' and students' financial constraints and their educational goals due to the financial burden (Adams et al., 2024; Lekan, 2024). Making wise, high-quality, and efficient investments in people's education is vital for creating the human capital that will end extreme poverty, according to the (Adeyemo & Olateju, 2022; Akter & Roy, 2017; World Bank, 2024). In order to address the learning crisis and end educational poverty, the Nigerian government believes that it is necessary to assist young, energetic individuals in acquiring the sophisticated cognitive, socioemotional, technical, and digital skills necessary to thrive in the modern world (Adams et al., 2021). Additionally, any government hoping to achieve sustained growth and development in their country must invest in the development of human capital. Using financial resources and putting social intervention programs into place to increase low-income people's access to education is one of the key tactics in Nigeria's long-term growth plan (Aina, 2002; Baker et al., 2017). Because of this, the Nigerian government introduced the Student Loan Program in 2023, primarily to assist students who are unable to pay for tuition, books, housing, food, and other expenses associated with their education (NELFUND, 2023). The students' loan program was established to break down financial obstacles to higher education and to advance educational equity and accessibility in accordance with the nation's economic growth and development roadmap (NELFUND, 2023). Many nations throughout the world have set up student loan programs to help students with their financial needs and make sure that access to education is not impeded by financial or economic restraints (Akumu, 2017; Panikar, 2016). To assist students in need, the Nigerian government has established programs like the Nigerian Student Loan Board (NSLB) and other financial funding organizations (NELFUND, 2023). The NELFUND determines loan eligibility based on Nigerian citizenship, enrollment in a public tertiary institution, and adherence to application procedures, including providing necessary documentation like National Identification Number (NIN), Bank Verification Number (BVN), and Joint Admissions and Matriculation Board (JAMB)/Matriculation numbers. Applications are reviewed, and successful applicants receive payments for tuition fees and upkeep, while those with past loan defaults or fraudulent activities may be denied. Notwithstanding these initiatives, the nation's student loan acceptance and approval rates are still shockingly low, which raises a number of concerns about the factors compromising the program's ability to effectively address educational disparities. But when students look for loans to pay for their requirements or academic fees, a number of variables become problematic. Bureaucratic delays, strict eligibility requirements, a limited loan offer, and a lack of knowledge about the scheme's accessible programs are some of the difficulties. These difficulties have led to a system in which a small percentage of students who applied for loans were successful in getting them, leaving many students without hope and limiting the development of the nation's human capital (Avery & Turner, 2012; Kossey & Ishengoma, 2017).

However, the absence of predictive modelling technique like logistic regression to model the main factors affecting loan approvals of Nigeria students using NELFUND data has created a research gap. Furthermore, there is an urgent need to streamline student loan approval procedures given Nigeria's rapidly increasing tertiary education enrollment in order to guarantee that funding reaches qualified applicants in a timely and equitable manner (Agbelusi, 2023). Due to the urgent necessity, a study that focuses on the variables influencing loan approval rates is required. Thus, the objective of this study is to model the approval rate of student loans from tertiary institutions in Nigeria, with an emphasis on determining the major factors that affect loan approval decisions. By investigating how predictive models can be utilized to expedite the loan approval process, lessen biases, and increase accessibility for eligible applicants, this study seeks to offer practical insights for stakeholders in higher education, financial institutions, and politicians.

The next section presented the theoretical framework of the study and empirical literature review. The fourth section provided research methodology, followed by the fifth section, which presents the results then the section for discussion of findings. Lastly, the conclusion and recommendation from these results were provided.

THEORETICAL FRAMEWORK

The Nigerian Education Loan Fund (NELFUND) and its effects on students at higher education institutions can be observed through the prism of the Human Capital Theory. According to McConnell et al. (2009), people with greater education, training, and skill levels are better positioned to contribute more productively to the job market. This demonstrates the fundamental tenet of NELFUND: funding Nigeria's future education is not only a social benefit but also a viable economic development plan. The theory of human capital was formally introduced by Schultz (1961), who also emphasized the importance of education as an investment tool. The theory was expanded upon by Becker (1964), who claimed that varying degrees of education and training lead to varying employment and income opportunities. In order to increase an individual's productivity, Becker once more claimed that human capital, like physical capital, could be acquired through training, education, health advancements, and even migration. In light of this approach, the NELFUND project can be viewed as a national initiative to develop Nigeria's human capital. The government wants to remove the financial obstacles to higher education by offering interest-free loans to students. This will enable more Nigerian youth, who make up the majority of the country's population, to acquire the skills, knowledge, and abilities necessary to support innovation and economic growth. Later, Ulrich (1998) contended that human resources should no longer be viewed as expenses to be reduced but rather as vital resources that create value in the future. Additionally, (Davenport, 1999) discussed the elements of human capital that are improved by higher education, such as intelligence, general and specialized knowledge, skill, talent, behavior, and effort. As Human Capital Theory predicts, NELFUND exposes students to opportunities that improve these traits, preparing them for future work opportunities and higher income levels. Essentially, NELFUND is in line with the Human Capital Theory since it understands that funding education will benefit the economy in the long run, not just for the immediate beneficiaries but also for the advancement of the country. According to the theory, Nigeria is economically creating a better, more innovative, and more competitive human force that will drive national growth by expanding access to higher education.

Empirical Literature Review

Numerous studies have examined factors impacting loan approval rates for students using various methodologies. Results from these studies have shown mixed findings regarding factors that affect students' loan approval rate.

Onen et al. (2015) looked at the difficulties students in a few chosen African nations have getting their loans approved. Data was gathered through desk research and literature searches. According to the study's findings, loan schemes in Africa face a number of issues in addition to the typical legal challenges that almost all student loan programs seem to encounter. These issues include the inability to establish trustworthy loan boards, find the right loan recipients, calculate suitable loan amounts, establish trustworthy databases, and set up efficient and successful loan disbursement and recovery systems. According to the study's findings, the political, social, and economic institutions in Africa are at the heart of the issues that African student loan programs confront. Unless these structural issues are resolved, these programs will encounter tremendous obstacles. de Gayardon et al. (2019), studied the degree to which student loan take-up is associated with family income, parental education, gender, ethnicity, debt aversion, and indices of family wealth (property ownership, private schooling, not residing in an impoverished area, and social class) is estimated. The only one of these that is proven to have no independent influence is social class. The study discovered that depending on the kind of debt, these correlations may vary. The study also reveals that although students from certain underprivileged groups are less likely to take out maintenance loans, this correlation can be explained by the fact that living at home while studying is a common way for students to avoid debt. Froidevaux et al. (2020) examined student loan approval using archival data from 1,248 graduating seniors from four geographically disparate US universities. According to the study, college seniors' chances of landing a full-time job after graduation were inversely correlated with their likelihood of experiencing financial pressure and, consequently, job search stress. Dosalwar et al. (2021) used data from Kaggle and a logistic regression model to predict whether a loan will be approved or denied. The findings showed that applicants are more likely to be granted loans if they have a high income and make smaller demands. Harper et al. (2021) examined the information sources that college students use when making decisions about their loans and financial aid based on data from 25 undergraduate students who were interviewed at a single public four-year university. The findings show a wide range in the quantity and type of sources that students use. Students felt that their access to help was woefully inadequate in almost every instance. Black et al. (2023) estimated the strength of the relationship between student loan take-up and family income, parental education, gender, ethnicity, debt aversion, and indices of family wealth (property ownership, private schooling, not residing in an impoverished area, and social class. The only one of these that was determined to have no independent influence was social class. The results also indicate that students from certain underprivileged groups are less likely to take out maintenance loans, and that these relationships can vary depending on the form of debt. Additionally, some research has persisted in examining student loans and the variables that influence their acceptance or rejection. Mahmoud et al. (2024) investigated the psychological aspects influencing Ghanaian students' decisions to take out student loans and their effects on graduation rates. The data employed in the study was collected by a purposive sample strategy from 114 pupils in Ghana. Result indicated that positive sentiments regarding student loans and plans to use them are positively correlated. Perceived behavioral control has no discernible effect on loan decisions, but subjective norms do. Additionally, there is a favorable correlation between loan decisions and graduation rates, indicating that loans can improve academic persistence. Obunadike et al. (2024) looked at the lending policies of five randomly selected nations. In order to execute the Nigeria Education Loan Fund (NELF) effectively, it was intended to gather pertinent data on the strengths and shortcomings of the student loan programs in those nations. According to the report, the majority of student loan programs in Africa confront a number of challenges, including the establishment of a trustworthy lending board, the identification of appropriate loan recipients, sustainability, a trustworthy database, the implementation of an efficient loan disbursement system, and debt recovery. Fadtare et al. (2024) use machine learning and predictive modeling approaches such as logistic regression, decision trees, random forests, and neural networks to study the automated and streamlined process of students' loan approval. The findings showed that important factors like income, credit score, employment status, and loan amount influence whether a student's loan is approved or denied. Ogunode et al. (2024) examined the impact of the Nigerian student loan scheme for postsecondary education on Nigeria. It was found that, the Nigerian student loan program will improve access to university education, boost the country's workforce, build up its infrastructure, hire more academic staff, and lower the prevalence of social vices among young people. Ayoko (2025) looked into the advantages and drawbacks of student loans in Nigerian higher education. The study came to the conclusion that increasing access to postsecondary education, cutting down on government spending, curbing social vices, and promoting economic growth are the advantages of student loans at Nigerian postsecondary institutions. The students also determined that the main variables influencing loan availability are insufficient financing, corruption, and payment delays.

Based on the reviewed studies above, the following hypothesis was proposed:

Hypothesis of the Study

H_0: Education, CIBIL score, income loan amount and bank assert value have no significant impact on students' loan approval.

Table 1. Variables' description and codes

Roles	Variables	Level	Descriptions
Dependent	Loan status	Rejected Approved	Loan status of the student sourcing for the student loan
Independent	Education	Not Graduated Graduate	Educational status of student sourcing for student loan
	CIBIL score	Quantitative	CIBIL score of student sourcing for student loan
	Income per annum	Quantitative	Income per annum of the student sourcing for student loan
	Loan amount	Quantitative	The amount the student is sourcing for
	Bank asset value	Quantitative	Bank asset value of the student sourcing for student loan

RESEARCH METHODOLOGY

Source of Data

The data used in this study are the monthly student loan status, CIBIL score (Credit score that shows the students 'creditworthiness), annual income, loan amount, bank asset value, and loan status obtained from Nigeria Education Loan Fund (NELFUND) (NELFUND, 2023), for period January, 2015 to July 2023 making a total of one hundred and three (103) observations with 55 Approval and 48 rejections. The dataset was collected through a combination of online application by students and data verification by tertiary institutions in Nigeria. **Table 1** provides the dependent, independent variables, students' level of study and the description of each variable utilized in this study.

Binomial Logistic Regression

When the explanatory variable being predicted is dichotomous (i.e., yes/no, pass/fail, male/female, success/failure, promoted/not promoted, high/not high, alive/dead, approved/rejected), binomial logistic regression, commonly known as logistic regression, is employed. Any number of continuous or categorical explanatory variables can be employed with the binomial logistic regression model. The generalized linear model (GLM) class includes binomial logistic regression. Using one or more explanatory variables, which may be continuous or categorical, binomial logistic regression attempts to predict the likelihood that an observation will fall into one of the categories of a dichotomous response variable.

Logistic Regression Model

To examine the connection between the independent factors and the binary outcome variable, a binary logistic regression model was selected. Because it can model binary outcomes of the loan status and estimate the likelihood of the outcome based on predictor factors, logistic regression is useful in this situation. The logit transformation, often known as the logistic regression model, converts the linear component to the log-odds of the success probability. The following are the model's specifications:

$$log\left(\frac{P}{1-P}\right) = \Sigma_{k=0}^{k} x_{ik}\beta_{ik}\,, i = 1,2,\ldots,N \tag{1}$$

where p is the probability of the outcome variable being 1 (loan approved), x_{ik} represents the predictor variables, β_0 is the intercept, and $\beta_i$represents the coefficients associated with each predictor.

$$\begin{aligned}\text{logit}\,(P) &= \log\left[\frac{P(x)}{1-P(x)}\right] \\ &= \frac{\beta_0 + \beta_1 X_{Education} + \beta_2 X_{Cibil\,Score} + \beta_3 X_{Income\,Per\,Annum} + \beta_4 X_{Loan\,Amount} + \beta_5 X_{Bank\,Asset\,Value}}{1-\beta_0 + \beta_1 X_{Education} + \beta_2 X_{Cibil\,Score} + \beta_3 X_{Income\,Per\,Annum} + \beta_4 X_{Loan\,Amount} + \beta_5 X_{Bank\,Asset\,Value} + e_t}\end{aligned} \tag{2}$$

Model Evaluation and AUC-ROC Analysis

The AUC-ROC curve is used in assessing the model's classification accuracy, as it captures the model's ability to distinguish between the two classes of the outcome variable in the model.

Receiver Operating Characteristic (ROC) Curve

The Receiver Operating Characteristic (ROC) curve is a plot of the true positive rate (sensitivity) against the false positive rate (1 - specificity) across different classification thresholds. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold values. These are defined as follows:

True positive rate (TPR), or sensitivity:

$$TPR = \frac{True\ Positives}{True\ Positives + \ False\ Negatives} \tag{3}$$

True negative rate (TNR), or specificity:

$$TNR = \frac{True\ Negatives}{True\ Negatives + \ False\ Positives} \tag{4}$$

False positive rate (FPR), or 1-specificity:

$$FPR = \frac{False\ Positives}{False\ Positives + True\ Negatives} \tag{5}$$

Area under Curve (AUC)

The AUC is the area under the ROC curve, ranging from 0 to 1. An AUC value close to 1 indicates excellent model performance, while an AUC close to 0.5 suggests no better performance than random guessing. The AUC represents the area under the ROC curve. While the AUC itself does not have a single formula, it can be approximated by summing the areas of trapezoids formed by successive points on the ROC curve.

Classification Accuracy

Accuracy measures the proportion of correct predictions (both true positives and true negatives) among the total predictions:

$$Accuracy = \frac{True\ Positives\ + True\ Negatives}{Total\ Predictions} \tag{6}$$

Precision and Recall

Precision and recall measure the proportion of true positives among all positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives\ + \ False\ Positives} \tag{7}$$

Measures the proportion of true positives among all actual positives.

The ROC curve and AUC score provide a summary of the model's effectiveness in distinguishing between the outcome classes.

Table 2. Descriptive statistics for the numerical variables

Variables	N	Min	Max	Mean	Variance	Std Dev
CIBIL score	103	300	861	567.68	29.514	5.43
Income per annum	103	300,000	990,000	5277.03	890.793	29.85
Loan amount	103	900,000	3,760,000	1582.60	950.610	39.78
Bank asset value	103	100,000	1,280,000	5099.13	754.562	27.47

Table 3. Logistic regression model parameter estimates and odd ratios

Explanatory variables	Parameter Estimates				Odd Ratio
	Estimate	Std. Error	Z value	p-value	Exp(B)
Intercept	21.372	2.734	21.372	.000	.000
Education	.620	.830	12.557	.018*	1.858
CIBIL score	.023	.005	24.174	.000**	1.024
Income per annum	-.561	.000	.091	.764	.0961
Loan amount	.731	.000	.510	.475	.003
Bank asset value	.712	.000	.555	.456	.001
-2 Log likelihood = 5342					
Chi-Square = 33.7, p-value = .312					

Significance codes: ***0.001, **0.01, *0.05.

RESULTS

Descriptive Statistics

Table 2 provides the descriptive statistics for the Numerical variables in the study. The variables are CIBIL score, income per annum, loan amount, bank asset value with 103 number of observations each. The minimum value for the variables is 300, 300,000, 100,000 and 900,000 respectively. The maximum values are 861, 990,000, 3,760,000 and 1,280,000 respectively. The mean value for the variables is 567.68, 5277.03, 1582.60 and 5099.13 respectively showing the values for the variables are around this mean values. The variance for the variables is 29.5, 890.793, 950.610, and 754.562 respectively revealing how the data elements vary from the mean values for each variable. The standard deviation for the variables is 5.43, 29.85, 39.78 and 27.47 respectively revealing how the data elements for each variable deviate from their means.

Logistic Regression Result

Table 3 shows the results from the logistic regression analysis. In this study, the student loan decision was the dependent variable, whether or not a student loan request was approved or rejected. This study examined the effects of the students' education level, CIBIL score, income per annum and loan amount on the likelihood of either rejection or acceptance of a loan request. The -2 Log likelihood ratio and chi-square results were also presented in **Table 3**. The -2 Log likelihood ratio is 5342 and the chi-square statistic of 33.7 is statistically significant ($p > .001$). Thus, the model shows that it is statistically significant in a student loan's request.

In this study, it was hypothesized that students' education level, CIBIL score, income per annum and loan amount would be associated with student loan requests.

Education Level

The logistic regression results show that the coefficient associated with education level was positive and statistically significant, indicating that students who are still in school were more likely to get student loan request approved than graduated students (Odds Ratio = 1.858 and p-value = .018 < .05).

Table 4. Performance of a classification test of logistic regression model the loan status

Test Statistics	N	Sensitivity	Specificity	Precision	Accuracy
Value	103	0.9583333 (95.83%)	0.9636364 (96.36%)	0.9636364 (96.36%)	0.961165 (96.12%)

CIBIL Score

Similarly, the result indicated that the students' CIBIL score was positively and statistically significant. This result implies that students with high CIBIL score were more likely to get their loan request approved than those with less score (Odds Ratio = 1.024 and p-value = .000 < .001). As the level of the students' CIBIL score increases, their chances of getting loan approval also increases.

Income Per Annum

Table 3 shows that the coefficients associated with income per annum were negative and statistically insignificant. As the student's income per annum increased, the students were less likely to get their loan application request approved (Odds Ratio = .0961 and p-value = .764 >.05).

Loan amount

Loan amount was also found to be statistically insignificant. This mean that, student that have requested for a large amount of loan were less likely to get a loan approval compared to those who have requested for a smaller amount of loan (Odds Ratio = .003 and p-value = .475 >.05).

Bank Assets Value

In the same vein, bank asset value proved to be statistically insignificant. The implication of this result is that students with lower bank assets were less likely to get loan approval compared to those who have higher bank assets (Odds Ratio = .001 and p-value = .456 >.05).

Table 3 shows the result from the logistic regression model parameter estimates and its statistics, In the table, the following logistic regression model were obtained:

$$\begin{aligned}\text{logit}\,(P) = \log\left[\frac{P(x)}{1-P(x)}\right] = P \\ = e\text{^}(21.4 + 0.6200 * Education\ + 0.023 * CIBIL\ Score + 0.561 \\ * Income\ perAnnum + 0.731 * Loan\ Amount + 0.712 * Bank\ Asset\ value\end{aligned} \tag{8}$$

The logistic regression model in terms of sensitivity and specificity, which evaluates the overall performance of the model, is shown in **Table 4**. The model successfully detected 95.8% of the positive cases, according to the sensitivity analysis, and 96.4% of the true negative cases, according to the specificity result. While high specificity indicates fewer false positives, this high sensitivity rate implies fewer false negatives. The ROC curve is another tool used to show this outcome (see **Figure 1**). According to **Table 5**'s Cox and Snell R^2, = 0.611, education, CIBIL score, annual income, loan amount, and bank asset value all sufficiently explained 61.1% of the variation in the log odd ratio. Fitting the independent variables explained 81.6% of the variation in the log odd ratio, according to the Neglereke R^2 = 0.816. Additionally, the model's McFadden R^2 = 0.684 suggests that it is an excellent match and accurately classifies 68.4% of all cases. The logistic regression model's receiver operating characteristics (ROC) curve for loan status is displayed in **Figure 1**. The curve displays the model's ability to discriminate between classes at various thresholds (specificity and sensitivity). The model detects the majority of true positives while limiting false positives, as shown by the figure's sharp early spike. **Figure 2** shows the AUC value of 0.9742, or 97.42 percent, which indicates that the model is doing well. The model performed optimally, according to the area under the curve (AUC) curve output, which was 0.9742. The binary

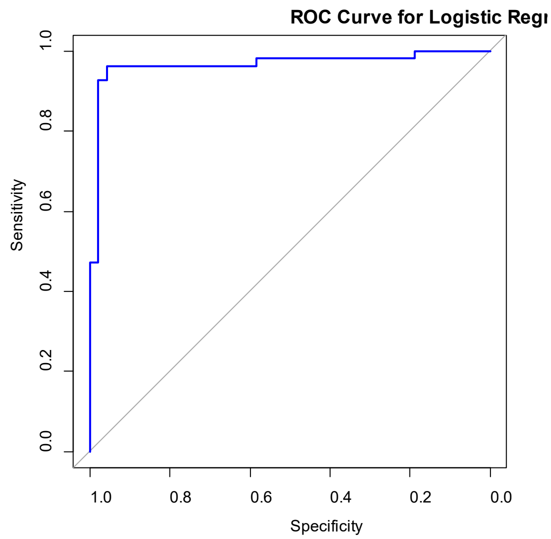

Figure 1. Graph of logistic regression for receiver operating characteristics (ROC) curve

Table 5. Model summary output

Regression Statistics	McFadden	McFaddenAdj	Nagelkerke	CoxSnell
Value	0.6840423	0.5997206	0.816418	0.6113679

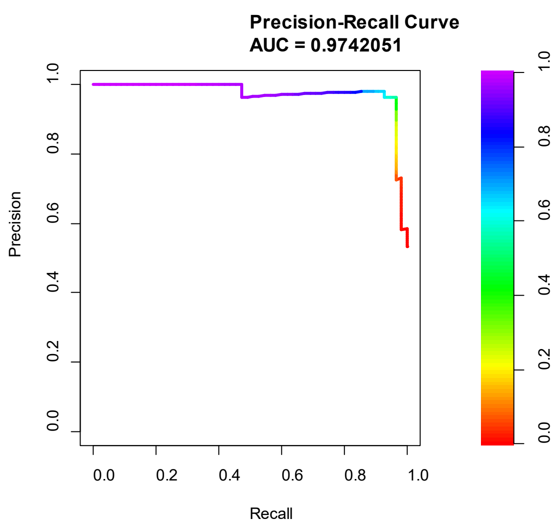

Figure 2. Graph of logistic regression for area under curve (AUC)

classification model's performance is gauged by the area under the curve (AUC). Approximately 97.42% of the time, a randomly chosen positive case (accepted) is more likely to have a higher predicted probability than a randomly chosen negative case (rejected), demonstrating the model's excellent predictive power and the ability of its predictors to accurately classify the loan outcomes. The logistics model's residuals graph is shown in **Figure 3**, and the model's projected probabilities plot is shown in **Figure 4**. The logistic regression model's estimated probability for the two loan status result classes (approved and rejected) was contrasted in the histogram. Whereas the overlap in the middle indicates misclassifications or model ambiguity, the red indicates actual class 0 (rejected outcome) and the cyan represents actual class 1 (approved outcome). The majority of predictions match their actual classes, indicating that the model performs rather well.

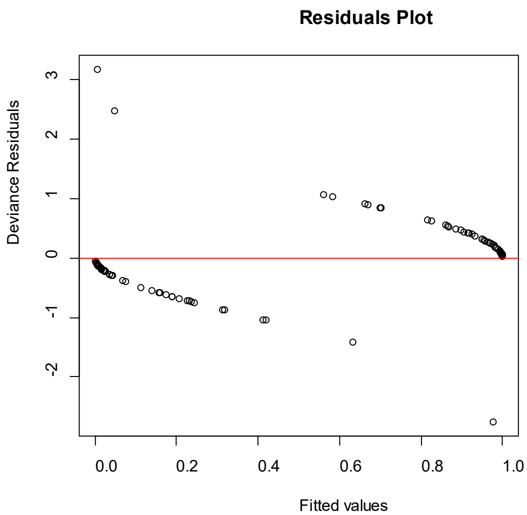

Figure 3. Graph of residuals

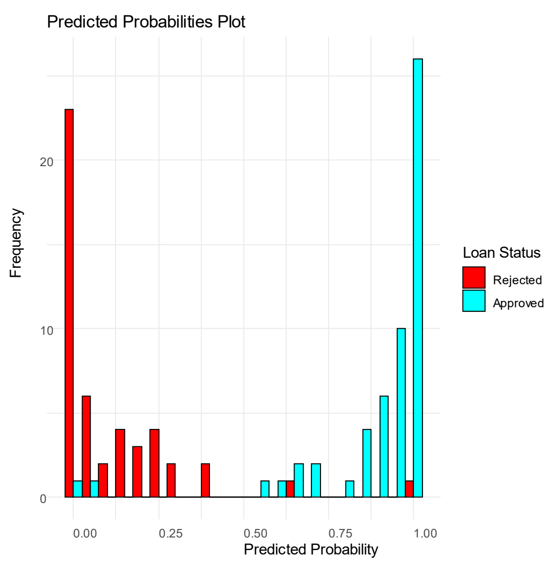

Figure 4. Graph of the predicted probabilities plot

DISCUSSIONS

This study utilized binary logistic regression technique to model the odds of tertiary institution school loan application approval rate based on factors like education status, CIBIL scores, income per annum, loan amount and bank asset values. Result revealed that education level was positive and statistically significant, indicating that undergraduate students were more likely to get a student loan request approved than the graduated students. This finding is corroborated by studies from (Brennan et al., 2013; de Gayardon et al., 2018; Mahmoud et al., 2024). Our result also found that students' CIBIL score was positively and statistically significant. Meaning that students with high CIBIL score were more likely to get their loan request approved than those with less score. To validate this finding, study by Fadtare et al. (2024) and Sheikh et al. (2020) found that crucial features such as job status, credit score, income, and loan amount determine whether a students' loan will be accepted or rejected. The coefficients associated with income per annum were found to be negative and statistically insignificant meaning that, as students' income per annum increased, the students were less likely to get their loan application request approved. Result also indicated that students that have requested for a large amount of loan were less likely to get loan approval compared to those who have requested for a smaller amount of loan. These findings corroborated Fadtare et al. (2024) that investigates students' loan approval using machine learning techniques and predictive modeling techniques like logistic regression, decision trees, random forests, and neural networks. Result indicated that crucial features such as job status, credit score, income, and loan amount determine whether a students' loan will be accepted or rejected. Our result was in agreement with findings of (Dosalwar et al., 2021; Sheikh et al., 2020) whose study found that students with high income and smaller loan request are likely to get a loan approval. Bank asset value proved to be statistically insignificant which implies that students with lower bank assets were less likely to get loan approval compared to those who have higher bank assets.

CONCLUSION

This study employs a binary logistics regression model to simulate the loan approval rate for Nigerian students enrolled in postsecondary institutions. Using data from the NELFUND online database, this study examined the factors that influence student loan acceptance. The study's primary factors were bank asset worth, annual income, loan amount, educational status, and CIBIL score. Based on the characteristics taken into consideration, the study used the binary logistic regression to model the likelihood of loan approval. Descriptive statistics showed that the sample's CIBIL score, income per annum, loan amount, bank asset value had 103 observations each. The minimum value for the variables is 300, 300,000, 100,000 and 900,000 while the maximum values were 861, 990,000, 3,760,000 and 1,280,000 respectively. The mean value for the variables is 567.68, 5277.03, 1582.60 and 5099.13 respectively showing the values for the variables are around this mean values. The variance for the variables is 29.5, 890.793, 950.610, and 754.562 CIBIL score, income per annum, loan amount and bank asset value respectively. The Sensitivity and Specificity values of 95.83% and 96.36%, respectively, demonstrated that the model was successful in identifying loan approvals and rejections, indicating good predictive accuracy according to the model performance criteria. The model's outstanding performance was validated by the AUC value of 0.9742, which showed that it could accurately and precisely distinguish between loans that were accepted and those that were rejected. The model's explanatory power is estimated to be 81.64 percent, demonstrating the model's goodness of fit. The Nagelkerke R-squared (R) is 0.8164, meaning that 81.64% of variations in the loan status are explained by the predictor variables (education status, CIBIL score, income annually, loan amount, and bank asset value). Result also indicated that 46 students had their loan status predicted to be rejected and actually rejected, while two respondents had their loan status predicted to be rejected but approved, according to the logistic regression classification table for the loan status. Additionally, 53 respondents had their loan status predicted to be approved and approved, while two respondents had their loan status predicted to be approved but rejected. This demonstrates that, with four instances of misclassification, the model accurately identified the loan status of 53 respondents as granted and 46 respondents as refused. The model outperformed random guessing by a significant margin, as shown by the cumulative gain (Lift) chart, especially when it came to recognizing authorized loans in the highest percentiles of the anticipated likelihood. According to the study's findings, a student loan's possibility of being approved is mostly determined by their educational level and higher CIBIL score. Additionally, the study found that non-graduates were more likely to be granted loans than graduates, indicating that educational status had significant effect on loan acceptance. In spite of the fact that loan approval is crucial in financial decision-making, other criteria including income, loan amount, amount of loan requested and bank asset worth did not significantly affect loan approval in this study. Additionally, the logistic regression model utilized in this study had excellent overall performance, exhibiting high levels of accuracy, precision, specificity, and sensitivity. According to the model's performance measures, it may be a useful instrument for forecasting the results of loan approval. It is suggested that future research should test predictive models on separate datasets or use cross-validation.

RECOMMENDATIONS

In light of the study's conclusions, it was suggested that:

1. NELFUND needs to make applicant creditworthiness (Cibil Score) a top priority in their approval process. They should be open and fair about how they use it.
2. NELFUND should take another look at how they use parental education level and money-related factors (income and assets) in their criteria. This study didn't find these to be key predictors. If they keep using them, they need to explain why.
3. NELFUND should put money into better ways to gather and study data. This will help them keep improving their risk models using the information they get from their operations

IMPLICATIONS

This study has important implications for universities since its implementation will simplify the process of disbursement, which requires institutions to accommodate different academic schedules, and it will ease the financial strain on students during disturbances like strikes. Although students must reapply for each session, the move to session-based loan disbursement emphasizes the need for protection to protect students in the event that academic schedules are disrupted and attempts to promote transparency and prevent duplicate payments. In order to maintain the integrity and success of the loan program, universities must work with NELFUND and take on more responsibility for confirming student information. By modeling NELFUND, policymakers can better understand how the loan fund affects equity, financial sustainability, access to higher education, and possible hazards like debt traps. This helps them to improve the scheme's efficiency, transparency, and inclusivity. Important ramifications include directing changes to policies, enhancing openness, resolving regional inequalities, guaranteeing sustained funding, and fortifying anti-corruption efforts through interagency cooperation with organizations like the EFCC. This study has implications for future research as well, including helping to inform policy decisions, enhancing the loan scheme's sustainability and efficiency, identifying and reducing potential risks like loan defaults and increased financial strain on students, and supporting data-driven approaches to national development by examining the effects on future economic competitiveness and educational access. Modeling can also show that in order to guarantee NELFUND's long-term success and keep its goal from being undermined, greater transparency, capacity building, and stakeholder involvement are required.

LIMITATIONS

The main source of limitations of this study is the incompleteness and inconsistency of the NELFUND data provided by Nigeria tertiary institutions, which has resulted in loan disbursements being delayed and applications being rejected. The absence of standardized academic calendars, the inability to administer maintenance loans consistently, and the possibility of data mismatch problems like inaccurate JAMB or matriculation numbers are among the difficulties. Additionally, NELFUND depends on higher institutions to submit timely and accurate data for verification, which leaves the procedure open to mistakes or delays in the pipeline for data submission.

In order to address the limitations, institutions need to integrate data, improve student account validation, improved communication, robust data management, and stakeholder engagement. Specifically, tertiary institutions need to upload academic calendars and student data promptly and accurately, while students must update their bank details to conventional accounts to ensure timely disbursement of loans and upkeep payments. NELFUND also needs to establish effective stakeholder engagement, conduct regular policy evaluations, and ensure transparency in its operations to enhance efficiency and maintain data integrity.

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