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Credit Risk Management and Loan Approval Decisions in Banking Institutions: A Governance-Based Perspective

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ABSTRACT

This research seeks to explore the impact of credit risk factors on credit approval decisions in financial institutions, and particularly to understand these decisions from a governance perspective. This research adopts a quantitative approach, analysing a secondary dataset sourced from Kaggle, consisting of 5,000 individual borrowers' data. The analysis is performed using Python, including descriptive statistics, correlation, logistic regression and machine learning (random forest). The findings show that credit score and income are the most important factors in loan approval, with credit score being the most influential. The significant skewness in approved and rejected loans indicates a risk-averse lending policy. In addition, machine learning approaches have higher predictive accuracy than classical statistical techniques. The research draws attention to loan approval systems as governance structures that implement risk management strategies in banks. The research highlights the need for incorporating sophisticated analytics in credit assessment. This research adds to the body of knowledge by connecting credit risk management to governance frameworks and provides a unique insight into how financial institutions govern credit lending.

KEYWORDS: Credit Risk Management**;** Loan Approval Decisions; Financial Governance; Banking Institutions; Machine Learning; Credit Scoring

1. Introduction

Banks are fundamental to economic growth, as they help to mobilise financial resources through lending activities. One of these activities, credit risk management, has become one of the key functions of financial institutions, as it affects institutional and financial system stability. Credit risk is the possibility that a borrower may not fulfil his or her financial obligations, which would lead to a loss for the creditor. To this end, financial institutions have established a range of tools to assess creditworthiness and manage the risk of default (Basel Committee on Banking Supervision, 2017). Sound credit risk practices not only protect financial institutions but also contribute to the financial sector's stability.

In recent decades, the growth in complexity of financial markets and the size of consumer credit have heightened the need for effective risk management. Banks and other financial institutions heavily use quantitative models and indicators of borrower characteristics, including income, credit scores, employment status, and loan size, to underwrite loans (Altman et al., 2017). These variables are used to guide structured decision-making systems used to approve or reject loan applications. These systems help ensure that institutional lending aligns with institutional risk and regulatory constraints, and thus lowers the risk of financial distress (Saunders & Allen, 2010).

As such, loan approval decisions are not merely operational decisions, but institutional risk management strategies. Such decisions are typically based on rules, scoring models, and thresholds that align with the institution's governance framework. Governance here refers to how institutions set policies, track risks, and ensure accountability for financial decisions (Shleifer & Vishny, 1997). By integrating risk management considerations into their decision-making, banks put governance policies in place to control lending practices and encourage prudent behaviour.

The increasing use of data mining and machine learning has also revolutionized credit risk management strategies. Predictive models allow banks to process significant amounts of information and detect relationships that might not be apparent using conventional statistical techniques (Lessmann et al., 2015). This enhances credit risk modelling and decision-making processes. Yet, they also pose challenges in terms of transparency, fairness, and governance, as algorithmic decision-making grows to impact and influence key financial decisions (Bussmann et al., 2021).

While these innovations have improved the efficiency of loan approval processes, decisions are still multidimensional and multifaceted. Variables like borrower income, credit score, job security, and demographic factors interact in complex ways, making it difficult to disentangle the effects of individual factors. Additionally, the existence of information asymmetry between borrowers and lenders adds to the complexity of the process, as banks rely on imperfect measures to gauge credit risk (Stiglitz & Weiss, 1981). Therefore, this knowledge of the impact of these variables in lending decisions is crucial to enhancing risk management and governance.

Meanwhile, from a governance standpoint, loan origination systems can be considered as institutional arrangements that impose risk discipline and policy adherence. Through their structured decision-making processes of approving or denying loan applications, banks manage credit risk and limit losses. From this perspective, it is essential to integrate risk management with governance, as effective control and accountability play a key role in ensuring financial stability

(Adams & Mehran, 2012; Van Gestel & Baesens, 2006). In this context, analysing loan approval decisions offers insights into the governance practices within financial institutions.

The existing research literature has provided a lot of attention to credit risk modeling and prediction, but less to governance issues associated with loan approvals. Much of the research concentrates on enhancing model accuracy or identifying important risk factors, while neglecting institutional factors (Crook et al., 2007; Khandani et al., 2010). Additionally, empirical studies often use proprietary data or very aggregated data sources, making it difficult to access borrower-level information. This leaves a gap in knowledge of how individual risk factors feed into governance-based lending outcomes in practice.

While there has been substantial progress in credit risk modelling and forecasting, there is a lack of integration of governance thinking in empirical studies of loan approval. The focus of previous studies is mainly on statistical fit and efficiency of the credit risk models, with little regard for governance perspectives on lending decisions. Moreover, there is a dearth of studies using publicly available secondary data to study borrower-level risk factors from a governance perspective. This underscores the need for studies that not only assess the factors influencing loan approval but also understand these decisions as tacit expressions of risk governance in banks.

In response to this gap, the present study aims to examine the relationship between credit risk factors and loan approval decisions using a secondary dataset obtained from Kaggle. Specifically, the study seeks to identify the key determinants influencing lending outcomes and to interpret these decisions from a governance-based perspective. By integrating quantitative analysis with a governance framework, the study contributes to a deeper understanding of how financial institutions operationalize risk management through structured decision-making systems.

2. Methodology

2.1 Research Design

This research follows a quantitative approach, which involves secondary data analysis, to investigate the link between risk factors and credit decisions in financial institutions. The study uses an explanatory design to understand the impact of borrower financial and socio-demographic variables on institutional loan decisions. The research also explains these loan approval decisions from a governance perspective, in which loan approval procedures are seen as institutionalised forms of risk control in the banking sector.

2.2 Data Source and Description

The empirical analysis is based on a secondary dataset obtained from Kaggle, titled *"Credit Risk & Loan Default Analysis Dataset."* The data contains 5,000 observations of loan applications and ten variables describing financial, employment and demographic information (Shahzad, 2026).

The variables in the dataset include age, income, loan amount, credit score, years of experience, gender, education level, city of residence, employment status and loan approval. The target variable LoanApproved is a binary indicator of whether the loan was approved (1) or rejected (0). The dataset represents borrower-level credit risk assessment data, and can be used to study institutional lending decision-making.

While simulated, the dataset is reflective of real-world practice in assessing credit risk and offers a good foundation for studying the risk management practices of financial institutions through approval processes.

2.3 Variable Specification

The research conceptualises loan approval outcomes as a product of credit risk factors and individual characteristics. The dependent variable is loan approval status, which captures the outcome of institutional decision-making processes.

Credit score, income, loan amount, employment type and experience are the independent variables and reflect important aspects of creditworthiness and risk. Credit score measures creditworthiness, income and loan amount represent borrower's ability to repay and risk exposure. Job type and experience reflect the stability and potential future income.

Age, gender, education and city are control variables that capture socio-economic characteristics that can affect loan approval. These variables help pinpoint the impact of key risk factors and enhance model performance.

2.4 Data Preprocessing and Cleaning

The dataset is pre-processed in Python before analysis. The dataset contains missing values in variables like income, credit score and education, which are imputed using suitable methods such as mean imputation for continuous variables and mode imputation for categorical variables.

Moreover, there are irregularities in the form of negative values in income and loan amount. These inconsistencies are resolved by either excluding invalid entries or converting them into valid values by making appropriate distributional assumptions. Categorical variables like gender, education, city and employment type are transformed using appropriate encoding methods, such as label encoding and one-hot encoding, to be used in statistical analysis.

The pre-processed dataset is checked for consistency, ensuring variables are in the right format for analysis.

2.5 Analytical Tools and Software

The data analysis is carried out using the Python programming language, with the assistance of libraries like Pandas for data manipulation, NumPy for numerical computing, Matplotlib and Seaborn for data visualization, and Scikit-learn for statistical modeling. Python is chosen for its versatility, reproducibility, and the availability of various statistical and machine learning methods, making it an ideal choice for credit risk analysis.

2.6 Statistical Techniques

The analysis uses descriptive, inferential and predictive statistical methods. The study begins with descriptive statistics used to describe the main features of the data, such as measures of centrality and variability, to gain an insight into loan applicant characteristics.

Next, Pearson correlation analysis is used to explore the interdependencies between independent variables and to check for multicollinearity. This is useful in assessing the correlation between risk indicators.

The main method of analysis employed in the study is logistic regression, as the dependent variable is binary. This model predicts the likelihood of loan approval based on credit risk factors and control variables. The logistic regression coefficients are interpreted to evaluate the associations between variables.

Besides logistic regression, some machine learning methods, such as decision tree and random forest classifiers, can be employed to improve the predictive performance and gain more insights into the decision-making rules. These approaches reveal non-linear patterns and decision rules that capture governance practices in lending.

2.7 Governance-Based Interpretation Framework

In this study, governance is conceptualized as the institutional framework through which financial decisions are structured and controlled. The decision-making processes for loan approvals are viewed as expressions of governance mechanisms that are driven by the rules for risk assessment. The study's examination of the impact of factors like credit score, income and employment status on loan approval decisions underscores how financial institutions translate governance into practice via uniform decision-making processes. This approach enables a more nuanced understanding of the translation of risk management principles into institutional policies in banks.

3. Results

3.1 Descriptive Statistics

Table 1 and Table 2 present the descriptive statistics of the variables of interest, which offer a glimpse into the characteristics of the borrowers in the sample. As shown in Table 1 and Table 2, this study includes 5,000 observations. Applicants' average age is around 43.58 years old, suggesting a relatively older borrower base. The average annual income is 49,760.37, with a large standard deviation, which implies diverse income levels.

The average loan size is 19,998.11, suggesting moderate levels of lending. The mean credit score is 575.63, with a standard deviation of 77.10 spread across a range of 300 to 849, suggesting a mix of riskier and less risky borrowers. Further, the mean experience is 19.59, implying that the applicants are experienced.

These statistics suggest the dataset represents a variety of borrower characteristics and allows for a detailed examination of credit risk and loan approval outcomes.

Table 1: Dataset Description

Variable	Data Type	Missing Values After Cleaning	Unique Values
Age	int64	0	52
Income	float64	0	4596
LoanAmount	float64	0	4561
CreditScore	float64	0	550
YearsExperience	int64	0	40
Gender	object	0	2
Education	object	0	4

City	object	0		4
EmploymentType	object	0		3
LoanApproved	int64	0		2

Table 2: Descriptive Statistics

Variable	N	Mean	Std. Deviation	Minimum	25th Percentile	Median	75th Percentile	Maximum
Age	5000	43.5846	14.9191	18	31	43	56	69
Income	5000	49760.37	14747.28	129	40036	49512	59447	99146
Loan Amount	5000	19998.11	7861.80	4	14599.75	19881	25326.75	48353
Credit Score	5000	575.63	157.41	300	440	579	706	849
Years Experience	5000	19.599	11.5168	0	10	20	29	39

3.2 Distribution of Loan Approval Decisions

Figure 1 below shows the distribution of loan approvals. This shows a large skew in the number of applications approved and rejected. There were 3,849 rejections and 1,151 approvals. This means that 77% of applications were denied, reflecting a conservative lending policy of the bank. This is indicative of sound risk management practices where only a small percentage of applicants fulfil creditworthiness standards.

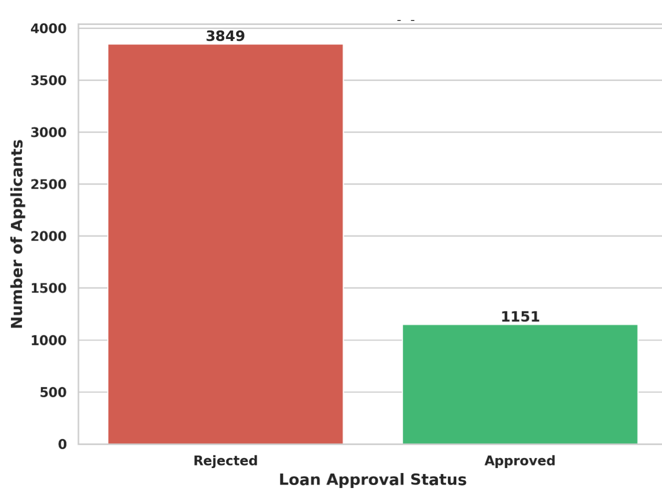

Figure 1: Distribution of Loan Approval Decisions

3.3 Credit Score Differences Across Approval Outcomes

The boxplot in Figure 2 illustrates the relationship between credit score and loan approval. The findings reveal differences between successful and unsuccessful loan applicants. The median credit score of approved applicants is much higher than that of rejected applicants.
Additionally, the interquartile range for approved applicants is shifted towards higher credit scores, whereas rejected applicants have lower and more variable credit scores. This suggests that credit score plays a critical role in loan approval, confirming that credit score is a major risk indicator.

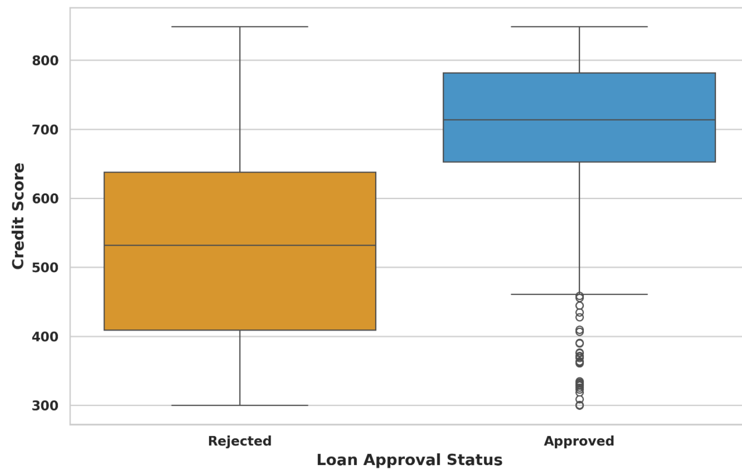

Figure 2: Credit Score Differences by Loan Approval Status

3.4 Relationship Between Income and Loan Amount

The scatter plot in Figure 3 shows the association between applicant income and loan amount, for both approved and rejected cases. The findings show that income is positively related to loan amount, meaning that individuals with higher incomes are inclined to apply for and receive larger loans.
But the presence of overlap between the approved and rejected cases indicates that income is not the only factor influencing the approval of loans. Rather, it is influenced by other factors like credit rating and job security. This observation lends credibility to the idea that banks use a holistic approach to risk assessment.

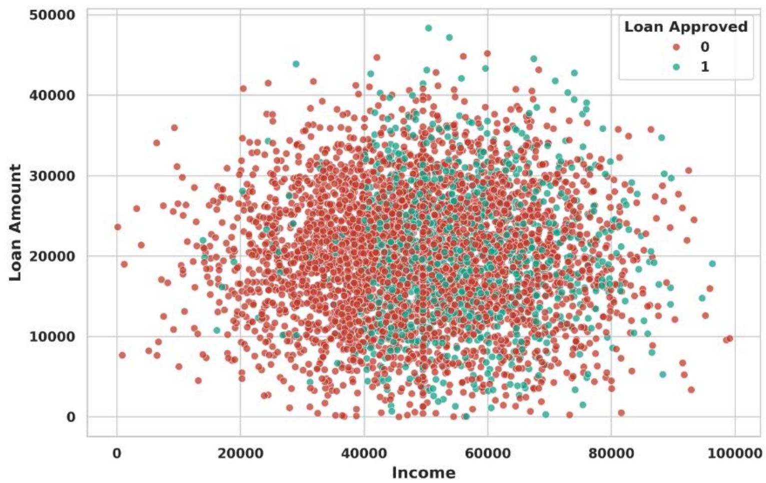

Figure 3: Relationship Between Income and Loan Amount

3.5 Correlation Analysis

Figure 4 shows the correlation matrix among the variables. It reveals that credit score exhibits the highest positive correlation with loan approval (r = 0.46), suggesting a moderate correlation.
There is a lower positive correlation between income and loan approval (r = 0.19), and negligible correlations with other variables including loan amount and years of experience. This indicates that credit score is the strongest predictor of the variables examined.
Crucially, there are no strong correlations among the independent variables, suggesting that there is no multicollinearity problem, and the regression analysis is valid.

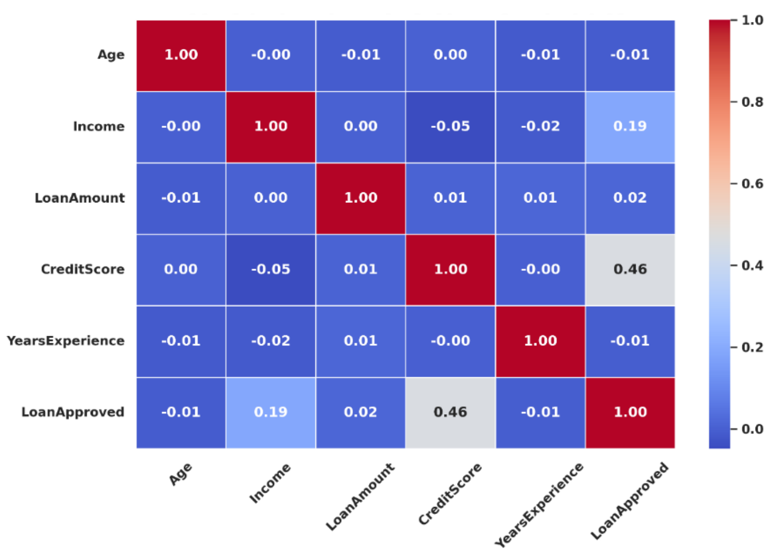

Figure 4: Correlation Matrix of Credit Risk Variables

3.6 Model Performance and Predictive Analysis

We used logistic regression and random forest models to assess the factors influencing the approval of loans. The results of these models are in Table 3.

The logistic regression model has an accuracy of 0.885, precision of 0.780, and recall of 0.696. This suggests the model is fairly effective in classifying approved applications, but there is still some room for improvement.

The random forest model, on the other hand, performs better, with an accuracy of 0.964, precision of 0.953 and recall of 0.887. The F1 score of 0.919 also confirms the model's good performance in predicting loan approval.

These findings indicate that non-linear and ensemble methods offer greater accuracy in predicting loan approval, and are able to capture non-linear relationships between risk factors better than linear models.

Table 3: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.885	0.780	0.696	0.736
Random Forest	0.964	0.953	0.887	0.919

3.7 Classification Performance (Confusion Matrix)

Figure 5 shows the confusion matrix for the logistic regression model. The model accurately predicted 725 rejected cases and 160 approved cases. But it incorrectly classified 45 rejected applications as approved and 70 approved applications as rejected.

This suggests that although the model is generally good, it tends to misclassify some of the approved applications, which may be due to the blurring of risk categories among these applications. This underscores to the challenges of credit risk management.

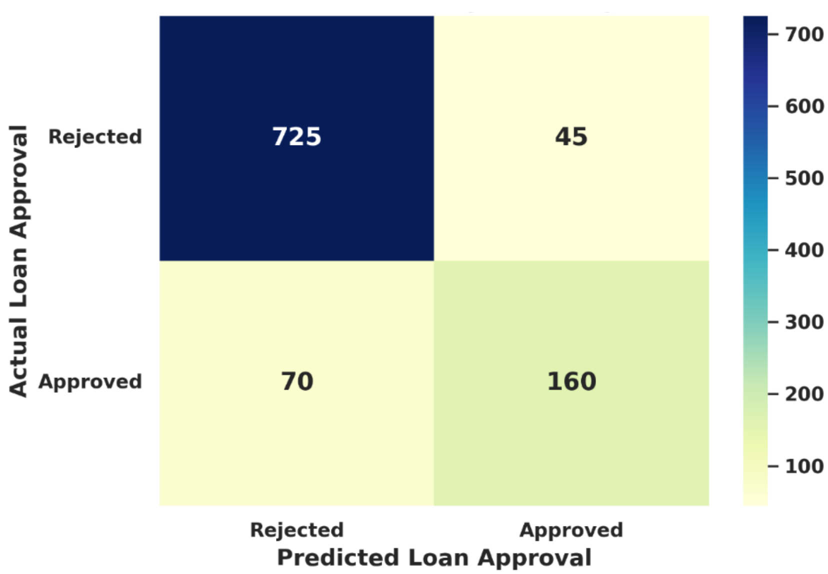

Figure 5: Confusion Matrix for Logistic Regression Model

3.8 Summary of Key Findings

The findings show that credit score is the most important factor influencing loan approval, followed by income (to a more limited extent). The highly skewed approval rate indicates a conservative approach by the bank. Also, machine learning techniques perform better than statistical methods, suggesting that loan approval decisions are affected by non-linear interactions between borrower attributes.

In summary, the results are consistent with the governance perspective of the study, in which loan approval decisions represent institutionalised mechanisms to manage financial risks in banking.

4. Discussion

The present study examined the determinants of loan approval decisions from a governance-based perspective using borrower-level credit risk data. The findings provide strong evidence that credit risk variables, particularly credit score and income, play a critical role in shaping lending outcomes. The results also highlight the institutional nature of loan approval decisions, reinforcing the view that such decisions function as structured governance mechanisms within banking institutions.

The most notable finding of this study is the preeminent role of credit score in loan approval. The correlation analysis showed that credit score is the most closely correlated variable to approval ($r = 0.46$), while the distribution analysis shows that approved loan applicants tend to have higher credit scores. This result is in line with previous studies highlighting the importance of credit scoring in the banking industry. Credit scores are used as a measure of borrower creditworthiness and are common in reducing the information gap between lenders and borrowers (Avery et al., 2004). Likewise, Abdou and Pointon (2011) report that credit scoring models play an important role in improving the efficiency and accuracy of credit decisions by offering objective risk measures (Abdou & Pointon, 2011).

Additionally, income was found to have a positive, but less significant impact on loan approval. This finding implies that while income is an indicator of borrower's ability to repay loan, it is not the only factor considered. This is consistent with the explanations offered by Agarwal et al. (2010) that income should not be relied on as the sole predictor of creditworthiness; other financial variables should be considered in conjunction with income (Agarwal et al., 2018). The interaction effect of income and loan amount also supports the view that lenders take a holistic view of borrower risk, considering several factors to make a risk assessment.

The disproportionate rejection rate of loan applications (around 77%) is indicative of a cautious approach to lending. This observation implies that financial institutions are cautious about credit risk and prefer to err on the side of risk management, especially in the face of economic uncertainty. This is in line with the risk-averse behaviour of banks, as previously documented (Berger & DeYoung, 1997). From a risk management perspective, the skew suggests the presence of tight internal controls and cut-offs aimed at reducing the risk from high-risk borrowers.

The predictive analysis also highlights the need for sophisticated analytical tools in credit risk modelling. Random forest had better performance in terms of accuracy, precision and recall than logistic regression. This indicates that the non-linear nature of the relationships and interactions between variables are important for loan approval. Our results are consistent with recent research that shows machine learning models outperform statistical models in credit risk assessment (Brown & Mues, 2012; Martens et al., 2007; Thomas, 2009). Machine learning models' capacity to capture complex relationships and patterns strengthens governance structures through improved and consistent decision-making.

The confusion matrix shows that although the logistic regression model is accurate in general, it fails to classify some of the approved and rejected applications. This error underscores the complexities of credit decision-making processes, in which marginal cases may display ambiguous risk factors. This highlights the need for considering multiple credit evaluation criteria and using sophisticated models to enhance decision-making. As Hand and Henley (1997) point out, credit scoring models are probabilistic and uncertainty can never be entirely eliminated in credit decisions (Hand & Henley, 1997).

The insights of this study are relevant to governance in financial institutions in terms of how they manage risk. The process of approving loan applications can be interpreted as institutional governance mechanisms that institutionalise policies and allocation decisions. The analysis of borrower attributes against predetermined criteria codifies a decision process that enhances transparency and governance. This perspective is consistent with the literature on governance of risk, which highlights the importance of internal controls and decision-making rules in managing risks (Power, 2007; West, 2000).

Moreover, data-driven modelling is an example of the growing digitalization of governance. Algorithmic-based decision-making allows financial institutions to handle a high volume of applications while applying consistent decision rules. Yet, this use of algorithms also presents challenges in terms of transparency and fairness, as discussed in recent research on algorithmic governance (Fuster et al., 2022; Zhou et al., 2009). It is crucial that these systems are transparent and fair to ensure trust and accountability in financial institutions.

In the context of existing literature, this study's results not only confirm the findings of prior studies about the significance of credit scoring, but also add to the body of research by adopting a governance-based approach. This study is different from existing research that primarily focuses on predictive performance by highlighting the institutional setting of lending decisions. This helps to broaden the view of credit risk management by linking technical aspects with governance.

While the study provides valuable insights, it has some limitations. First, the study uses a synthetic dataset from Kaggle, which might not account for all the intricacies and variations in banking data. Although the data includes realistic credit risk scenarios, it does not contain detailed institutional and macroeconomic factors that might affect lending.

Second, the analysis is largely confined to borrower characteristics, and does not include bank-level governance factors such as board composition, regulatory adherence or risk management policies. So, governance is assessed implicitly through lending decisions, rather than explicitly.

Third, the study is cross-sectional and does not permit the investigation of dynamic aspects of credit risk management. This would allow a more comprehensive understanding of the dynamics of risk management in response to the business cycle and regulatory changes.

Researchers can build on the insights of this study by using a wider array of variables at the individual and institutional level. Inclusion of governance measures like board structure, risk management committees and regulatory frameworks would offer a direct measure of governance in banking.

Moreover, future research could investigate the effects of macroeconomic variables (such as interest rates, inflation and economic cycles) on loan approvals. This would further improve the understanding of the impact of external factors on risk management.

Future studies could also explore the use of emerging machine learning methods, such as deep learning and explainable artificial intelligence (XAI). These techniques can enhance prediction accuracy, while increasing explainability and interpretability in decision-making.

Finally, future studies may explore ethical issues and biases in algorithmic lending. With the growing use of algorithmic systems, financial institutions must ensure that their systems are fair and transparent for sustainable governance.

5. Conclusion

This research focused on the impact of credit risk variables on loan approval decisions of financial institutions, taking a governance-based approach. The study shows that credit score is the most influential factor, followed by income, whereas other factors like loan amount and experience have a lesser impact on the loan approval decision. The significant class imbalance of approved and declined loan requests also suggests that banks tend to have a conservative lending policy, driven by robust institutional governance. Additionally, the research shows that machine learning techniques, such as random forest, are more effective than logistic regression for predicting the outcome of loan applications. This suggests a need to integrate sophisticated data analytics in credit risk assessment to improve decision-making and performance. In terms of governance, loan approval decisions are not just operational processes but formalised processes through which financial institutions implement risk discipline and adhere to policies. In conclusion, the research adds value to the existing literature by linking credit risk assessment with a governance perspective, providing a holistic view of institutional decision-making. While the study has limitations due to data limitations and the lack of explicit governance measures, it offers insights for practitioners and academics seeking to enhance risk mitigation in financial institutions.

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