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A Critique of the Influence of the Loan Model on Asset Quality in Zimbabwe Commercial Banks

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ABSTRACT

This paper investigates the influence of several loan models, namely Credit Score, Z-Score, and Asset-Based Lending, on asset quality in Zimbabwean commercial banks. The study was driven by constant challenges, including high non-performing loan (NPL) ratios, economic volatility, regulatory inconsistency, and limited borrower credit histories. In Zimbabwe's particular macroeconomic context, the study assesses loan performance using a mixed-methods approach, combining quantitative surveys (n = 406) with qualitative interviews with 24 risk officers. Results show that although proactive loan modelling improves client assessment and lowers credit risk, outside variables, including inflation, political unrest, poverty, and limited technology, compromise model performance. Based on factor analysis, strong credit risk control depends on proactive and reactive elements. The study finds that in Zimbabwe's banking environment, model fit rather than lifetime determines effectiveness. To raise asset quality and lower NPLs, it advocates more model integration, ongoing observation, and alignment with economic reality.

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1. Introduction

Commercial banks are vital for economic stability as they facilitate credit creation, financial intermediation, and investment (Meher & Getaneh, 2019). In developing economies like Zimbabwe, efficient loan models are crucial for maintaining asset quality, liquidity, and financial stability. These models help reduce credit risk, ensure loan repayment, and sustain bank profitability. Over the past two decades, Zimbabwe's banking sector has undergone significant changes due to economic volatility, hyperinflation, and financial reforms (Makoto, 2020). Economic instability, according to Ofria and Mucciardi (2022), has often led to an increase in non-performing loans (NPLs), which weaken bank capital and lead to financial distress. To combat this, banks have implemented various loan models such as relationship lending, transaction-based lending, credit scoring and asset-based models to improve asset performance and lower default rates (Ferreira, 2023). However, the effectiveness of these models in Zimbabwe's context is still debated. Despite financial sector reforms, Zimbabwean banks continue to face challenges with high NPL ratios, which peaked at 20% in 2015 before corrective measures were introduced (Moses & Dicky, 2024). Various loan models have been employed with mixed results on asset quality and financial stability. While several studies have examined bank performance and credit risk management in emerging markets, there is a paucity of research specifically evaluating the influence of different loan models on asset and loan performance in Zimbabwe (Sani, 2025).

Existing literature tends to focus on broad financial stability measures without critically assessing the effectiveness of loan models in managing global default risk and improving asset quality. This study aims to fill this gap by offering a focused critique of the

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influence of the Loan Model on Loan Performance in Zimbabwe Commercial Banks. Studies suggest that the success of loan models is influenced by economic conditions, regulatory frameworks, and institutional capabilities.

Relationship lending can enhance creditworthiness assessments in African banking markets, while transaction-based models are effective for high-volume lending (Kolawole, 2025). In Zimbabwe, inconsistent regulations, currency instability, and low financial literacy among borrower's complicate loan performance (Marimira & Gumel, 2025). The country's banks operate in a challenging macroeconomic environment with liquidity constraints, fluctuating exchange rates, and unpredictable policies, leading to high default rates (Aledeimat & Bein, 2025). These are often due to economic instability. Furthermore, insufficient credit histories and difficulties in collateral enforcement paralyse loan management and or performance. Understanding how loan models affect asset performance is essential for developing effective credit risk management strategies.

This study seeks to evaluate the effectiveness of loan models in managing asset performance in Zimbabwean banks. It explores the relationship between loan models and NPLs and examines the regulatory and economic factors affecting loan model performance. Ultimately, the goal is to comprehensively assess how loan models influence loan and asset performance in Zimbabwe's banking sector. By analysing different lending strategies and their impact on financial stability. Therefore, the study seeks to inform banking policies and risk management practices that improve credit quality and asset sustainability.

2. Literature Review

2.1 Zimbabwean Financial Institutions and Banking Sector

Between 2010 and 2018, Zimbabwe's banking sector experienced significant instability, causing banks such as CFX Bank, Premier Bank, Genesis Investment Bank, and Interfin Bank to collapse. Tetrad Bank and Metbank also faced significant challenges due to unpaid loans, known as non-performing loans (NPLs) (Leesurakarn, 2021). These problems were mainly due to poor asset quality, weak management of credit risk, ineffective corporate governance, and a lack of sufficient capital. The loan models used at the time failed to prevent defaults (Jin, 2021). Post-dollarisation (post-2009), Nyandoro et al. (2023) observed a steady deterioration in credit quality, with NPLs peaking at 20% by 2015, far exceeding the Basel II benchmark of 5% (Basel Committee on Banking Supervision, 2004). This decline in loan performance led to a loss of public trust and resulted in over 1,000 bank employees losing their jobs between 2009 and 2014, when six banks closed. The crisis attracted government attention, with industry leaders, including former Bankers Association President George Guvamatanga, urging reforms to ensure lending practices meet international standards (Makowani, 2011). Despite these issues, Zimbabwean banks continue to use traditional methods to evaluate creditworthiness, such as Internal Credit Scores, Z-scores, and Asset-Based models. These methods are useful for discovering profitable enterprises and forecasting bankruptcies.

However, critics highlight significant flaws. Z-score models often fail to detect manipulated financial data and become less accurate over time (Maniatis, 2022). Similarly, Credit Score models based on neural networks or expert systems are criticised for being opaque and subjective, leading to inconsistent outcomes (Sumanth & Sharan, 2024). Banks in Zimbabwe continue to face significant hurdles, both from within and from external factors they can't control. For instance, political unrest, soaring inflation, and fluctuating interest rates make it tough for borrowers to keep up with their loan repayments (Nweke & Bakare, 2025). On top of that, banks often deal with outdated technology and slow legal processes when trying to recover collateral from defaulted loans. Environmental and social changes, like new sustainability regulations, add even more strain on the performance of loans if these factors aren't included in risk assessments (Selim & Alshareef, 2025). A major issue under discussion is the disconnect between banks claiming adherence to proper loan models and the ongoing problems that persist. This study explores whether these models are suitable for Zimbabwe's unique economic challenges and strict regulatory environment, or if they inadvertently contribute to worsening asset quality. The focus is on determining whether loan models are truly aligned with the realities faced by borrowers and the external risks present in the environment.

3. Research and Methodology

3.1 Models

3.1.1 Loan Models

This paper will examine three models, namely: Credit Score, Z-score, and Asset-Based. The performance of bank loans is an overview of bank loans and the way these loans are categorised as either performing or non-performing loans (NPLs), including the causes of such categorisation. Thus, the loan model's effectiveness reflects the way banks measure the efficiency of the loan model in use.

3.1.2 Credit Score Model

According to Sriram (2022), the Credit Score model is a statistical technique used in predicting the probability that a person who applies for credit will eventually default or become delinquent; a methodical way of assigning scores in line with default probabilities of a prospective borrower. The scores of the model show the client's capacity to service a monthly loan instalment or not, based on set benchmarks. Any system used to evaluate the risk associated with a borrower produces credit scores assigned to borrowing clients that exhibit the risk level of the prospective borrower to the lender (Fine, 2024). The rationale of scoring is to ensure aspiring borrower risk levels are detected within a short timeframe, particularly where consumer lending is concerned. These definitions also reveal

that no standard variables are used when applying this method, suggesting that any item or aspect that identifies a risk threatening the repayment capacity of a borrower can be weighed.

3.1.3 Z-Score Model

This model is defined by Al-Najjar and Jawad (2023) as a quantitative measure for forecasting the bankruptcy or failure of a financial entity. According to Braunsberger and Aschauer (2025), the Z-score model may also be referred to as "a linear combination of four or five common financial ratios, weighted by coefficients". The key element of the Z-score model is its ratios, as set out below:

Z=1.2A+1.4B+3.3C+0.6D+1.0E

X1=Working capital /total assets

X2=retained earnings /total assets

X3=earnings before interest and taxes /total assets

X4=market value of equity /book value of liabilities

X5=sales/total assets

For a public company, when the Score is 3.0 or above, it suggests bankruptcy is unlikely, resulting in a positive lending decision. However, should the Score be 1.8 or less, the company should not be granted a loan, as it may go bankrupt within the next two years. In a private manufacturing firm, when the Score is 2.90 or above, the company is good for credit, but when the Score is 1.23 or below, the risk is high (Gerwanski, 2020). The classification of clients is based on the cut-off value, and all the variables should be positive to attain a good Z-score.

3.1.4 Asset-Based Model

As explained by Rodima-Taylor (2022), Asset-Based Lending is a revolving loan; the facility is bargained for upfront, and the bank takes cognisance of assets owned by the borrower as a source of repayment. The assets are consecutively revealed in the borrowing base certificate, which shows categories and the nature of assets pledged as security. Any loan advancement or receivable asset that is secured and monitored, as well as valued, such as inventory, is referred to as Asset-Based Lending (Huang, 2023). Furthermore, it is a formula-based model whereby lending is placed against acceptable assets, such as receivables and inventory, with the financier controlling cash collections, thus reducing its exposure to the borrower. Additionally, Asset-Based Lending allows for informed decision-making, matching loans to be granted with the prospective client's cash conversion cycle. Nsamba and Tumuhaise (2025) define Asset-Based Lending as an example of transactional lending. This form of lending is backed by security that may include various assets in the form of stock and debtors. However, it is prudent to also observe business operations. All the definitions illustrate that the solid foundation of Asset-Based Lending is centred on assets, pledged as the source of primary repayment if instalments are not paid on time.

3.1.5 Effectiveness of Loan Models

According to Schweser (2012), the prediction performance of the Credit Score model (internal) and the Asset-Based model can be measured using the following formula: in other words, use computing to assess the credit rule by calculating the number of defaults that were accurately predicted and the number of firms that were predicted to default but did not.

The formulae are, respectively:

1. Y = Number of defaults correctly predicted

   Number of defaults

2. X = Number of firms predicted to default and did not

   Number of firms that did not default

Applying the Y and X symbols indicates how a two-dimensional graph would illustrate results. A maximum value of unity is shown in the graphical representation for the X and Y axes. Whereas the X-axis signifies the incorrectly predicted default proportion, the Y-axis denotes that of defaults correctly predicted. Z-score effectiveness is validated through an ordinal score, which is the aggregate of the decile scores and corresponding bankruptcy percentage within x years, for each decile. Restaino and Bisogno (2019) state that in relation to the variable under measurement, its intensity, values and levels, ordinal scales offer some order. There is also a sense of ranking within these measures; therefore, the higher the ordinal score, the greater the model's ability to distinguish those most likely from those least likely to go bankrupt. The following formula was proposed by Restaino and Bisogno (2019) to establish the effectiveness of loan models such as Z-Score:

X=Σ PBK xi

i=1

Where:

PBK = number of companies in decile i that went bankrupt within x years

i,x = total number of companies that started in decile i

Continuous values, from zero, where there is no drift and maximum stability, to 10, with complete drift and no stability, can be acquired by this ordinal score. A lower percentage demonstrates model effectiveness.

Loan model effectiveness is measured by comparing results recorded against set benchmarks or cut-offs (Gumbo & Zoromedza, 2016). Furthermore, the model should minimise Type I and Type II errors, wherein a Type I error ensues when the future failure of a client is not identified or predicted by the model, whilst a Type II error denotes the classification of a creditworthy client as a likely bad debt, and the application is declined. Therefore, some predefined characteristics should be used to measure the performance of a loan model.

3.2 Bank Loan Performance

A bank loan is money given to businesses or individuals, with specific rules for repayment (Worku, 2021). These rules include the time you must pay back, typically ranging from one to seven years, but sometimes extending to 20 years. During this time, both the original amount and interest must be repaid by set dates. Various factors influence a commercial bank's decision to approve loans for different sectors. One such key factor is liquidity, which Bianchi and Bigio (2022) explain as the cash a bank has available to meet loan requests. When many people request loans, the bank's liquidity decreases. With fewer loan requests, banks hold onto more short-term or liquid assets. However, when loan requests are high, banks tend to reduce liquid assets because long-term loans can be more profitable. Therefore, a bank's ability to issue loans is better when it has ample cash reserves. Interest rates are also crucial for banks. Ogundele and Nzama (2025) pointed out that these rates, which represent the cost of securing a loan, help decide if a loan will be approved. This implies that borrowing and lending depend on customers' ability to afford the loan and repay it on time. Higher interest rates make loans more costly. Loans are classified into two types: performing, which means they are being repaid as scheduled, and non-performing, which means they are not being repaid as agreed.

3.2.1 Performing Loan

A performing loan is paid back on time, including the interest (Oppusunggu, 2022). Even if a loan is up to 90 days late, it still counts as performing, which means the bank can record the interest as income (Ademola, 2024). There are three main parts to a performing loan, and one of them is the Agreement. Both the borrower and the bank sign this contract, specifying the loan amount, interest rate, and payment schedule. Additionally, some covenants require the borrower to submit financial documents like management accounts, records of debts and credits, and stock returns. The bank uses these documents to keep track of the borrower's financial situation (Kassegn & Endris, 2022).

3.2.2 Security

Security is an asset used as a fall-back position by a bank, and the type and value should be precise (Wolters & Jacobs, 2019). The loan agreement on the required security is precise (Arauz, 2021).

3.2.3 Interest and Principal

Principal is the amount of the loan that remains unpaid at any given time, which means it is effectively the total amount the bank disburses to the client (Ibad, 2024). However, whenever a client makes monthly repayments, the principal amount decreases, and the principal balance is expected to have a zero balance at the final date of the loan term. Additionally, any margin or return on principal that is profit generated from loans extended to clients is referred to as interest. An example of how interest is calculated is shown:

I=A x i/c x N

Where:

I=total interest charge over the life of the loan

A=amount of loan

i/c=contractual interest rate per timeframe

N=number of periods covered by the loan.

3.2.4 Non-Performing Loans

The instant when a loan ends with earnings to a lending institution is classified as an NPL (Moeed & Afjal, 2024). This indicates that the asset continues to operate over and above the approved limit by the bank, while the interest and instalment are not serviced for 90 days. A good example is a farmer whose two cropping season instalments are unpaid because of recurring droughts.

The following are examples of financial factors that cause NPLs.

3.2.5 Interest Rates

Nugraheni and Risman (2025) observe that Non-Performing Loans deteriorate when interest rates soar, making it difficult for borrowing clients to service loans. For example, on 31 October 2013, the Zimbabwean government authorised banks to increase borrowing interest whenever necessary. All they had to do was seek authority.

3.2.6 Gross Domestic Product (GDP)

Greenwood and Hanke (2021) describe GDP as the fiscal price placed on any output that is goods or services at a particular time (year) in a country. All the goods and services are added to determine the market value when the economy performs. However, when the economy is depressed, unemployment increases, consumers' disposable income falls, and corporate revenues, which are sources of loan repayments, also decrease.

3.2.7 Inflation

Inflation is the frequency at which the prices of goods or services change (Dekimpe & van Heerde, 2023). The rate of price movement impacts consumer spending (cash flow) levels, as it determines affordability and the capacity of diminishing income, which incapacitates borrowers from servicing their loans, resulting in NPLs.

3.2.8 Exchange rate

The price of a different currency in a foreign exchange market is termed an exchange rate (Challoumis, 2024). Fluctuations in the exchange rate, where the trader imports most inputs, make products more expensive and result in low sales that reduce the capacity to service debts, with resultant NPLs.

3.3 Method

This study used a mixed approach incorporating both quantitative and qualitative research. Quantitative data were collected using surveys with closed-ended questions and a 5-point Likert scale distributed to loan department staff in 14 Zimbabwean commercial banks. The sample participants were selected using stratified sampling to ensure participation across managerial and operational staff members. The sample response rate was 81.2% response rate (406 of 500 questionnaires returned), deemed highly representative. To improve the research, instrument validity and reliability, a pilot test was conducted with 30 loan workers to help refine the questions before dissemination. Additional quantitative data were obtained from the bank's non-performing loan ratios, financial records, and bank closure and merger information. The questionnaire underwent pretesting and was evaluated with contributions from two academic specialists. Reliability was tested using Cronbach's alpha-tested survey item reliability, and factor loadings checked the alignment of survey questions with underlying concepts, aiming for values above 0.5 or, ideally, 0.7 (Sekaran & Bougie, 2009). The qualitative component of the study involved semi-structured interviews with 24 risk officers from active and defunct banks. Sample respondents with credit risk management expertise were purposively sampled as a defining factor. Interviews explored the participants' experiences with loan models, perceived efficacy, and factors influencing bank performance. A structured interview was developed to maintain consistency and match the quantitative survey questions, which banking experts reviewed to ensure completeness. These interviews provided depth and contextual richness, enhancing the comprehension of statistical results from the statistical data. Qualitative data was analysed using thematic analysis. NVivo software was employed to assist in organising and analysing interviews, revealing patterns, key themes and subthemes. Furthermore, NVivo software reduced manual duties, efficiently identifying trends and significant themes. This mixed-method approach was deemed appropriate as it better explains the relationship between loan models and bank performance (Creswell & Creswell, 2017). Despite employing a sequential explanatory design, data integration occurred during the analysis phase, facilitating comparisons between quantitative trends and qualitative insights.

4. Analysis and Findings

To analyse LPMM effectiveness and Loan performance in Commercial Banks in Zimbabwe, respondents were required to rate the extent of their agreement with a set of eight questions, with a 5-point Likert scale of variable responses, with 3.0 as the midpoint. The summary statistics for the eight items are given below (Table 1).

Table 1: Summary Statistics

	N	Mean	SD	Skewness	Kurtosis
To identify good clients	406	4.00	.773	-1.040	1.904
To ensure security adequacy	406	3.79	.945	-.800	.002
To determine the regular review of security	406	3.43	.874	-.051	-.615
To guide measures to be taken when a loan is in doubt	406	3.33	.868	-.135	-.460
To guide the assessment of the sister companies of a borrowing corporate client	406	3.36	.845	-.088	-.135
To determine non-performing loans	406	3.67	.880	-.658	-.094
To compare the performing loan to the total loan book	406	4.13	.742	-1.313	3.610

	N	Mean	SD	Skewness	Kurtosis
To predict bankruptcy	406	3.63	.876	-.869	-.021
Valid N (listwise)	406				

Source: Author's construction

The outcome shows all the items were rated above 3.0, which indicates respondents agreed all the items demonstrated LPMM effectiveness. The major effect was seen with the item "compare performing loans to the total loan book", with a mean rating of 4.13 (SD = 0.742). The standard deviation was the least, and this was an indication of considerable consensus among respondents. This was further confirmed by the high skewness statistics of -1.313 and the high positive kurtosis of 3.610. The second-highest rated item was the item "to identify good clients" (M = 4.00; SD = 0.773), with the second-lowest standard deviation among all the items and the second-highest positive kurtosis (Kurt = 1.904), which again showed consensus among respondents. With both variables having positive kurtoses, this meant both distributions were, therefore, leptokurtic in nature. The third highest rated item was "to ensure security adequacy" (M = 3.79; SD = 0.945), while the fourth highest rated was "to determine NPLs" (M = 3.67; SD = 0.880) and "to predict bankruptcy" was rated fifth (M = 3.63; SD = 0.876). The kurtoses for these three variables were approximated to zero; that is, 0.002, to ensure security adequacy, -0.094 to determine NPLs and -0.021 to predict bankruptcy. In other words, the distribution for these three items was mesokurtic. However, the least-rated item, albeit positively rated, was "to guide on measures to be taken when a loan is in doubt" (M = 3.33; SD = 0.868), while the second least was "to guide on assessment of sister companies of a borrowing corporate client" (M = 3.36; SD = 0.845), with the third least-rated item "to determine regular review of security" (M = 3.43; SD = 0.874). For these three, there was a high negative kurtosis of -0.615, -0.460 and -0.135, respectively, and the distribution was platykurtic, which meant there was no consistency in the responses.

4.1 Factor Analysis

With a view to identifying the key factors that demonstrate the effectiveness of LPMM, EFA was again carried out, using PCA as the extraction method (Howitt & Cramer, 2017). To validate the use of EFA, the KMO test for sampling adequacy and Bartlett's test for sphericity were performed, and the outcome (Table 2) was presented.

Table 2: KMO Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.732
Bartlett's Test of Sphericity	Approx. Chi-Square	625.289
	Df	28
	Sig.	.000

The results show that KMO = 0.732, while for the Bartlett's test, $\chi 2$ (28) = 625.289; $p<0.05$. Since the KMO was greater than the prescribed minimum of 0.50, along with Bartlett's test significance being less than the prescribed 0.05, the results confirmed that the assumptions for the use of EFA were not violated. The PCA was used as an extraction method, and the Varimax orthogonal rotation method was performed. Communalities are presented in Table 3.

Table 3: Communalities

	Initial	Extraction
To identify good clients	1.000	.518
To ensure security adequacy	1.000	.530
To determine the regular review of security	1.000	.781
To guide on measures to be taken when a loan is in doubt	1.000	.761
To guide the assessment of the sister companies of a borrowing corporate client	1.000	.090
To determine non-performing loans	1.000	.578
Comparing performing assets to the total loan book	1.000	.444
To predict bankruptcy	1.000	.684

Extraction Method: Principal Component Analysis

Only one of the items is illustrated as having a commonality extraction less than the prescribed minimum of 0.40, the item "to guide on assessment of sister companies of a borrowing corporate client", whose commonality was 0.090 and flagged as a possible item for deletion. The extracted components are shown in Figure 1 below.

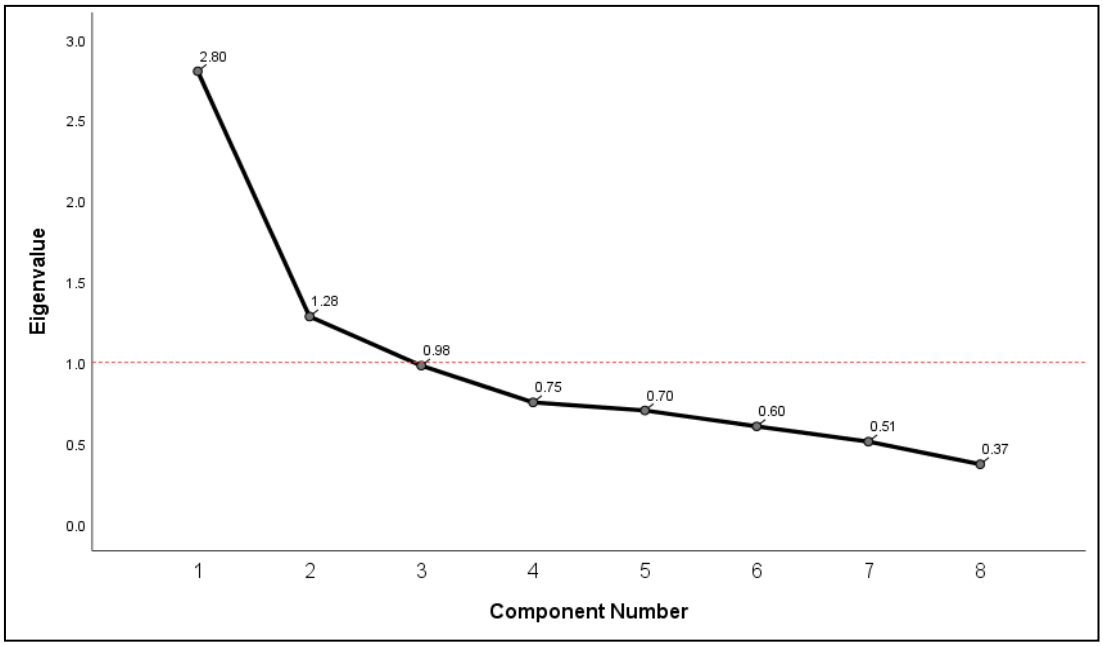


Figure 1: Scree Plot

Only two components were extracted with eigenvalues more significant than the recommended value of 1.0. The rotation sums of their squared loadings and total variance explained are presented in Table 4.

Table 4: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.802	35.021	35.021	2.802	35.021	35.021	2.420	30.250	30.250
2	1.284	16.047	51.068	1.284	16.047	51.068	1.665	20.817	51.068
3	.979	12.240	63.308						
4	.752	9.399	72.707						
5	.702	8.774	81.481						
6	.604	7.545	89.027						
7	.509	6.362	95.388						
8	.369	4.612	100.000						
Extraction Method: Principal Component Analysis									

The results show that for component 1, the eigenvalue was $\lambda = 2.802$, while the variance explained was 30.250 per cent. For component 2, the eigenvalue was $\lambda = 1.284$, and the variance explained was 20.817 per cent. Overall, the cumulative variance explained was 51.068 per cent, and since this was greater than the minimum expected value of 40 per cent, it meant the extracted components were valid. The rotated component matrix is presented in Table 5.

Table 5: Rotated Component Matrix

	Component	
	EBA	EBA
To determine performing assets	.760	-.011
To identify good clients	.715	.080
To ensure security adequacy	.667	.291
Comparing performing assets to the total asset book	.657	.108
To predict bankruptcy	.602	.146
To guide the assessment of the sister companies of a borrowing corporate client	.242	.177

	Component	
	EBA	EBA
To determine the regular review of security	.157	.870
To guide on measures to be taken when a loan is in doubt	.090	.868
Extraction Method: Principal Component Analysis Rotation Method: Varimax with Kaiser Normalisation		
Rotation converged into 3 iterations.		

Tavakol and Wetzel (2020) recommend that the factor loadings should be greater than 0.50, and from the above results, only one item had factor loadings less than this threshold across the two components. This was "to guide the assessment of sister companies of a borrowing corporate client", which had earlier been flagged for having a poor commonality. In this regard, the item was disregarded. For component 1, the extracted items were "to determine non-performing assets, to identify good clients, to ensure security adequacy, to compare performing loans to the total loan book and to predict bankruptcy". Component 2 comprised two items, that is, "to determine regular review of security" and "to suggest measures to be taken when a loan is in doubt". The findings reveal two extracted key factors that exhibit the effectiveness of LPMM. Identifying the common issues among the Component 1 items reveals that factor one comprises proactive measures that impact on the effectiveness of the loan model. Likewise, identifying the common issues among the component 2 items shows that factor two comprised reactive measures.

4.1.1 Loan Performance

The last aspect was evaluating loan performance, which was measured on a 5-point variable response Likert scale with the statistics summary presented (Table 6).

Table 6: Summary Statistics

	N	Mean	SD	Skewness	Kurtosis
Non-performing loans are caused by poor planning.	406	3.92	.751	-.851	1.573
Non-performing loans are a result of poor markets	406	4.12	.641	-.732	1.832
Non-performing loans are a result of poor cash flows	406	4.08	.641	-.633	1.474
Non-performing loans are caused by an outdated model	406	3.92	.748	-.764	1.025
Internally modified models have resulted in quality loans	406	3.74	.854	-.415	.093
Overall Loan Performance	406	3.96	.684	-.519	2.057

Source: Author's construction.

The results show all items rated higher than the midpoint of 3.0, generally reflecting a high level of NPLs, on the whole. The highest rating was "NPLs are caused by poor markets" (M = 4.12; SD = 0.641), followed by the item "NPLs are caused by poor cash flows" (M = 4.08; SD = 0.641). The third highest rating was that "NPLs are caused by poor planning" (M = 3.92; SD = 0.751) and that "NPLs can be caused by an outdated model" (M = 3.92; SD = 0.748). The lowest rating was that "internally modified models have resulted in quality loans" (M = 3.74; SD = 0.854). Overall, the aggregate rating was M = 3.96 (SD = 0.684) and being greater than the midpoint, the study confirms a very high level of NPLs. This is further supported by all the skewness statistics being negative, and, more importantly, the kurtoses were all positive, which showed the distributions of the responses were leptokurtic. In other words, there was a very high degree of consensus among the respondents regarding their ratings of the level of NPLs.

This result demonstrates the usefulness of a loan model towards loan performance as exhibited by its capacity to isolate potential bad clients at the outset and during a loan cycle or tenure, as one of the methods banks use to determine the effectiveness of loan models. PESTLE analysis was carried out to augment the analysis, which comprised political, economic, social, and technological factors, as well as legal environment and internal environment factors. The overall comparison across all these factors is presented (Figure 2).



Figure 2: Hierarchical Chart - Factors Affecting Effectiveness of LPM

The hierarchical chart above shows that the major factor that affected the effectiveness of the LPMM was the economic environment, followed by the social environment, while the third was the political environment. The legal environment, the internal environment, and the technological environment were also dominant.

4.1.2 Economic Environment

From Figure 2, six sub-themes were extracted under the economic environment, and among these, the most dominant was inflation. The unstable macro-economic environment was also mentioned as the second dominant factor based on the coding references, while the third was the absence of local currency, followed by interest rates, poor money supply, and the country's GDP. Inflation was reinforced by risk officers, who argued:

"The effectiveness of loan portfolio management models is primarily affected by inflation, which affects the purchasing power on the part of the borrowers, and in the case of Zimbabwe, where most salaries are not often adjusted to align with prevailing exchange rates, the depleted value of salaries negatively drives the default rate. On the part of the bank, inflation affects interest rates, and in a hyperinflationary economy like Zimbabwe, the originally agreed interest rates may be affected by emerging inflation rates, which in turn negatively affect the efficacy of the loan portfolio management models."

The shortage of local currency in Zimbabwe and the poor money supply all had a direct linkage to interest rates, which, in turn, directly and indirectly, affected the LPMMs.

4.1.3 Social Environment

Regarding the social environment, three sub-themes were extracted, which included social unrest, poverty and borrower behaviour. Participants largely mentioned the issue of poverty as influencing LPMM performance. There was a nexus between poverty and the economic environment, and risk officers explained:

"*The likelihood of default is high among borrowers who have a low revenue during the course of repaying the loans, attributed to their customers who have low income or become poor before the corporate borrower liquidates borrowings from a bank. Other high-risk borrowers are not detected earlier during the loan application screening stage, but owing to circumstances that might induce poverty, such as retrenchments or the salary-currency value misalignment, the disposable income becomes depleted, and this, more often, drives loan defaulting. The rate at which local currency salaries are adjusted upwards in most cases does not resonate with the rate at which the exchange rate changes, and as a result, the efficacy of loan models under such circumstances is directly affected. So yes, poverty is a major driver of poor loan portfolio management model performance*."

Borrower behaviour was also presented as a key driver of loan default, and sub-themes such as gender, age, ethnicity, and borrower financial situations, as well as borrower credit scores and credit card use, were also mentioned by the participants among the sub-social factors that influence the probability of loan default.

4.1.4 Political Environment

The political environment was the third dominant factor listed by participants as impacting LPMM. The four sub-themes listed included politically driven policies, politically exposed persons (PEP) risk, and politically motivated changes in laws, in addition to politically motivated changes in the currency regime. Several participants from closed banks, as well as from operating banks, argued that political risk was a key factor negatively affecting the LPMM performance and a key contribution was provided by risk officers as follows:

"Politically motivated, arbitrary policy pronouncements have often haunted Zimbabwe's banking sector for the past two decades. As the external debt mounted in the early 2000s, the Government responded by printing more money as a means to ease the cash shortages and to fund government operations, but this move had gross implications towards the economy as the inflation spiralled out of control to a peak of 489 billion% in 2008. The default rate became very high. While this later improved, the recent years have been characterised by the further devaluation of the newly adopted local currency in 2018, which economists consider as implemented prematurely without the necessary macroeconomic fundamentals in place. The new currency has recently started to have an impact on the NPLs, and if the situation is not resolved on time, the blame will be on the political environment."

The foregoing arguments do confirm that; indeed, some politically motivated policies that violate fundamental economic principles play a key role in the poor performance of LPMMs.

4.1.5 Legal Environment

In the legal environment, the key concerns raised by participants related mainly to the Government's proclivity to change laws that have an unintended, but direct bearing on inflation and the default rate by borrowers. This has been characterised of late by the approval of controversial laws that some economists disapprove of as violating the fundamentals of macroeconomics, as they have potential long-term repercussions, risk officers highlighted.

"The legal environment plays a key role in influencing loan default rates. Several examples can be drawn from past experiences, but most importantly, the recent legal aspects that have had a negative impact on the economy."

The preceding discussion tends to align well with the role that the political environment plays, as the changes in laws and regulations are largely spearheaded by political players.

4.1.6 Internal Environment

The internal factors in the bank were also mentioned as having a significant influence on the effectiveness of LPMMs. The main theme that emerged was management non-compliance, as evidenced by the sub-themes "not respecting model outcomes" and "management priorities". This was also corroborated by one of the closed bank participants, the closed bank risk officers, who argued:

"One of the challenges that we faced before the collapse of the bank was the failure of the management to respond in a timely manner to the model outcomes, but rather reverting to impulse-driven decisions in place of data-driven decisions. Often, the loan models provided useful predictive and prescriptive insights to ensure the effectiveness of loan portfolio management models is maintained; however, divergent priorities by the management overruled the action that was required from the loan model results."

Management, therefore, played a key role in the internal environment.

4.1.7 Technological Environment

The last factor was the technological environment, and from the outcome, two key sub-themes were extracted, namely data integrity and limited technological investment by the banks. One of the participants who explained this well was the risk officer:

The success of loan performance management models is largely affected by the accuracy of the model, and this is largely affected by the availability of quality training data, as well as the availability of the skills and technology that can assist with the computations. More robust business intelligence systems tend to be very expensive in terms of both the hardware and software licenses, and as a result, some banks might choose to use alternative systems, while in some cases, there could be a shortage of expert staff who can manage the training of the models as well as their deployment. Most important is the integrity and quality of the data used for training

the models. As they say, garbage in, garbage out (GIGO). It is, therefore, very vital to collect useful, detailed data if better models are to be developed and deployed."

Overall, where the technological environment is concerned, it can be confirmed that for some banks, this was an issue which was mainly affected by the integrity and quality of the data available, the robustness of the available systems for the modelling, as well as the technical expertise available. It can therefore be concluded that commercial banks assess the effectiveness of loan models by evaluating their capacity to fully assess the environment.

5. Discussion

The results show that for the relationship between LME and LP ($\beta = 0.736$, $p = 0.000<0.05$), LPMM under use by the Commercial Bank had a statistically significant relationship with loan performance. These results suggest that when the accuracy level of a loan model is higher, the probability of loan performance is almost guaranteed. Additionally, banks are likely to return such a useful tool to reduce potential debts in their loan portfolio. This work was thus two-fold. First, it was to establish aspects that demonstrate an effective loan model and second, loan performance. Quantitative analysis employed an extraction method that resulted in only two components being extracted. The first component comprised five items, which were all proactive aspects that demonstrate loan model effectiveness. These were to determine NPLs, identify good clients, ensure security adequacy, compare performing loans to the total asset book, and predict bankruptcy. The second component comprised only two items, deemed reactive measures, because they are applied to an existing loan, determine the regular review of security and suggest measures to be taken when a loan is in doubt. Items shown to be high-ranking in demonstrating the effectiveness of an LPMM were to compare performing loans to the total loan book, where a positive outcome should be obtained, to identify good clients, and to ensure security adequacy. These aspects connote that the loan model will facilitate a reduction of the number of defaulters and exposure, meaning the model is effective. The results show the bank must take both proactive and reactive measures into consideration for a loan model to be successful. The work further sought to determine loan performance, with results showing some NPLs attributed to various reasons, such as being in poor markets, poor cashflows, as well as an outdated model, among others. The results, therefore, demonstrate that even though the bank may have a robust loan model, as well as an applicant who passed the selection criteria, some unforeseen circumstances cannot be determined by a loan model, such as future markets of the borrower and when upset, clients may fail to service the debt. From the interviews conducted, key participants from both operational and closed banks agreed that, regardless of the type of model in use, for it to be considered effective, it should be able to facilitate the selection of only bankable projects. Furthermore, key informants from operational and closed banks anchored both the external and internal environment as deterrents to loan performance. Several other attributes that can show model effectiveness have also been identified in this study. These include a model that can recognize quality clients, which was discovered by (Hoai & Nguyen, 2022).

Accuracy is also propounded. To compare performing loans to the total loan book, where a positive outcome is obtained, it was ranked as the highest attribute of an effective model. This finding alludes to the position of Marrenbach (2024), who stated that the effectiveness of a loan portfolio model could be validated by comparing performing loans to the total loan book, where the positive results displayed confirm the model's impact. In evaluating loan performance, the study has shown that various reasons can cause poor loan performance. Poor markets came out as a strong reason for this, a finding made by Oo (2025), who observed that a small market share of business results in NPLs. Poor cashflows being generated by borrowers can further result in poor loan performance, a finding made by Alao (2025), who argues that inadequate cashflows cause NPLs, as borrowers might have limited capacity to repay the loan. Islam (2026) is of the view that it is not always the model's predictive ability that impacts loan performance. Factors such as delays in processing, behind-schedule loan disbursement, diversion of funds, and slow decision-making by managers that are slow can cause poor loan performance.

6. Conclusions

For a loan model to be deemed effective, it must be able to choose only bankable projects or creditworthy clients and provide adequate security (an active measure). Furthermore, the study argues that a bank should be able to continuously use a loan model during the tenure of a loan (reactive), enabling loan book monitoring using the model. Additionally, the study determined there were some NPLs in the banking sector, mainly due to an inadequate market for borrower products, the use of outdated models, and insufficient cash flows. The major factors that affected the LPM model's effectiveness were the external environment; economic, social and political were at the top of the list. There were also references to other environments such as internal, legal, and technological ones. In this study, external challenges overtake events of loan models; for example, high inflation depletes company revenues, hence reducing the capacity to service the debt. In addition, the unstable political environment is also a cause for concern. Malpractices internally were another factor highlighted as a major cause of NPLs due to management not respecting the loan model outcomes, resulting in overriding negative scores showing a potential defaulter(s). From the findings, it can, therefore, be argued that the number of years a model has been in existence is not what makes it effective in a country, but its suitability or capacity to evaluate targeted clients. Whilst the model may be effective at the onset, it may not be able to predict loan performance throughout the loan cycle. It is also evident from the study that while loan models may be effective at the onset of the loan, unforeseen market loss by the borrower upsets sales and causes NPLs (poor markets). The study also argued that an effective loan model promotes loan performance, ensures only creditworthy clients are afforded access to loans and makes certain there is adequate security on any borrowings. The Internal Credit

Scoring Model has been proven to be the most dominant model in Zimbabwe. This entails that for a prospective client to qualify for a loan; they have to satisfy the scoring model requirements and the minimum or benchmark score.

6.1 Areas of Future Recommendations

This study looked at the tools used to assess company loan applications initially. However, a more extensive study is needed to understand why some loans become non-performing loans (NPLs) and how they affect loan performance in commercial banks. An important area for further research is how internal bank factors contribute to NPLs. Banks have specific rules for loan disbursement, which include issuing facility letters, registering pledged security, and assessing liquidity. Delays in these processes can disrupt borrowers' financial plans, especially when loans are needed for urgent business activities. Investigating how these operational inefficiencies lead to loan defaults could provide valuable insights for improving risk management and credit control. Another area needing more research is the link between loan model effectiveness and a bank's operational tenure. A bank's ownership (local or multinational), technology skills, and market history can influence its ability to use credit assessment systems effectively. It would be useful to determine if older banks perform better with their loan models due to experience or if newer banks are better with modern technologies, offering insights into optimal banking practices. Research is also needed on the safety and reliability of loan rating systems. Since today's loan evaluations rely heavily on computer-based scoring models, cyberattacks are a significant risk to data integrity and lending decisions. Cyberattacks, data breaches, or system takeovers can compromise credit evaluations, leading to incorrect lending choices and higher NPL rates. Research should examine the weaknesses of digital loan assessment systems and evaluate how effective current cybersecurity measures are in protecting sensitive financial information. Securing loan scoring procedures is crucial for accurate credit risk assessments and maintaining trust in institutions. Addressing these topics can improve future research on NPL causes, loan model efficiency, and risk reduction techniques, thereby strengthening the financial stability of commercial banks.

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References

Ademola, A. O. (2024). Effects of loan terms and borrowers' behavior on non-performing loans in Nigeria's microfinance banks. Indonesian Journal of Business and Economics, 7(2). https://doi.org/10.25134/ijbe.v7i2.10815

Al-Najjar, S. M., & Jawad, M. K. (2023). Application of Z-score and Z-3 score models to evaluate the financial situation of the Modern Sewing Company: A case study. International Journal for Humanities & Social Sciences, 2, 46–57. https://doi.org/10.69792/IJHS.23.2.6

Alao, O. (2025). Data driven financial decision-making for minority enterprises: Capital access, investment strategies, and creditworthiness optimization. International Research Journal of Modernization in Engineering Technology and Science, 7. https://doi.org/10.56726/IRJMETS70930

Aledeimat, S. R. M., & Bein, M. A. (2025). Assessing US and global economic policy uncertainty effects on non-performing loans in MENA's Islamic and conventional banks. International Journal of Finance & Economics, 30(4), 4279–4304. https://doi.org/10.1002/ijfe.3121

Arauz, A. (2021). The international hierarchy of money in cross-border payment systems: Developing countries' regulation for central bank digital currencies and Facebook's stablecoin. International Journal of Political Economy, 50(3), 226–243. https://doi.org/10.1080/08911916.2021.1984728

Bessis, J. (2010). Risk management in banking (3rd ed.). John Wiley & Sons.

Bianchi, J., & Bigio, S. (2022). Banks, liquidity management, and monetary policy. Econometrica, 90(1), 391–454. https://doi.org/10.3982/ECTA16599

Bichanga, W. O., & Aseya, L. (2013). Causes of loan default within microfinance institutions in Kenya. Interdisciplinary Journal of Contemporary Research in Business, 4(12), 316–335.

Braunsberger, C., & Aschauer, E. (2025). Corporate failure prediction: A literature review of Altman Z-score and machine learning models within a technology adoption framework. Journal of Risk and Financial Management, 18(8), Article 465. https://doi.org/10.3390/jrfm18080465

Brown, & Moles, P. (2014). Credit risk management. Edinburgh Business School, Heriot-Watt University.

Challoumis, C. (2024). The transition from fixed to flexible exchange rates and its global impact. Procedia on Economic Scientific Research, 11, 164–179.

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). Sage.

Creswell, J. W., & Poth, C. N. (2018). Qualitative inquiry and research design: Choosing among five approaches (4th ed.). Sage.

Dekimpe, M. G., & van Heerde, H. J. (2023). Retailing in times of soaring inflation: What we know, what we don't know, and a research agenda. Journal of Retailing, 99(3), 322–336. https://doi.org/10.1016/j.jretai.2023.07.002

Ferreira, C. (2023). The influence of bank performance, market condition and economic growth on non-performing loans. World Journal of Applied Economics, 9(1), 77–98. https://doi.org/10.52970/grfm.v5i2.1211

Fine, S. (2024). Character counts: Psychometric-based credit scoring for underbanked consumers. Journal of Risk and Financial Management, 17(9), Article 423. https://doi.org/10.3390/jrfm17090423

Furnham, A. (1986). Response bias, social desirability and dissimulation. Personality and Individual Differences, 7(3), 385–400.

Gerwanski, J. (2020). Does it pay off? Integrated reporting and cost of debt: European evidence. Corporate Social Responsibility and Environmental Management, 27(5), 2299–2319. https://doi.org/10.1002/csr.1965

Greenwood, J., & Hanke, S. H. (2021). On monetary growth and inflation in leading economies, 2021–2022: Relative prices and the overall price level. Journal of Applied Corporate Finance, 33(4), 39–51. https://doi.org/10.1111/jacf.12479

Gumbo, V., & Zoromedza, S. (2016). Bank failure prediction model for Zimbabwe. Applied Economics and Finance, 3(3). https://doi.org/10.11114/aef.v3i3.1639

Hoai, T. T., & Nguyen, N. P. (2022). Internal control systems and performance of emerging market firms: The moderating roles of leadership consistency and quality. SAGE Open, 12(3). https://doi.org/10.1177/21582440221123509

Howitt, D., & Cramer, D. (2017). Understanding statistics in psychology with SPSS (7th ed.). Pearson.

Huang, C. (2023). Optimizing the performance of operations-finance interface by implementing supply chain finance schemes [Doctoral dissertation, The Hong Kong Polytechnic University].

Ibad, M. S. (2024). Analysis of the loan program of the savings and loan business unit at BUMDesa Mutiara Welirang, Ketapanrame Village according to the perspective of Sharia economics. Malacca: Journal of Management and Business Development, 1(2), 87–102. https://doi.org/10.69965/malacca.v1i2.98

Islam, S. (2026). AI-driven credit scoring and default probability modeling for Basel III risk-weighted asset optimization in banking. American Journal of Scholarly Research and Innovation, 5(1), 1–32. https://doi.org/10.63125/pkpawp97

Jin, T. M. (2021). Household indebtedness and non-performing loans in Malaysia [Doctoral dissertation, University of Malaya].

Kassegn, A., & Endris, E. (2021). Factors affecting loan repayment rate among smallholder farmers got loans from the Amhara Credit and Saving Institution: In the case of Habru District, Amhara Regional State, Ethiopia. International Area Studies Review, 25(1), 73–96. https://doi.org/10.1177/22338659211040993

Kilic, A. (2018). Can factor scores be used instead of total score and ability estimation? International Journal of Assessment Tools in Education, 6(1), 25–35.

Kolawole, K. (2025). Bank credit, lending costs, and the growth dynamics of SMEs in emerging economies. International Journal of Applied Research in Business and Management, 6(5). https://doi.org/10.51137/wrp.ijarbm.367

Lee, T., & Chen, I. (2005). A two stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. Expert Systems with Applications, 28(4), 743–752.

Leesurakarn, S. (2021). Non-performing loan regimes in banking regulation [Doctoral dissertation, University of Warwick].

Makoto, R. (2020). Financial integration and macroeconomic volatility in Zimbabwe. Journal of Economics and Development, 22(2), 229–248. https://doi.org/10.1108/JED-11-2019-0063

Makowani, N. (2011). An assessment of strategic planning by commercial banks in a multi-currency era: A case study of Barclays Bank of Zimbabwe [Master's thesis, University of Zimbabwe].

Maniatis, A. (2021). Detecting the probability of financial fraud due to earnings manipulation in companies listed in Athens Stock Exchange Market. Journal of Financial Crime, 29(2), 603–619. https://doi.org/10.1108/JFC-04-2021-0083

Marimira, N., & Gumel, B. I. (2025). Financial risk management in Zimbabwe. Asian Journal of Economics, Business and Accounting, 25(3), 337–348. https://doi.org/10.9734/ajeba/2025/v25i31714

Marrenbach, L. (2024). Leveraging credit ratings through impression management: An exploratory study of German small and medium-sized family firms. Junior Management Science, 9(2), 1511–1539. https://doi.org/10.5282/jums/v9i2pp1511-1539

Meher, K., & Getaneh, H. (2019). Impact of determinants of the financial distress on financial sustainability of Ethiopian commercial banks. Banks and Bank Systems, 14(3), 187–201. https://doi.org/10.21511/bbs.14(3).2019.16

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). Qualitative data analysis: A methods sourcebook (3rd ed.). Sage.

Moeed, A., & Afjal, M. (2024). Educational empowerment: Evolution, innovations and challenges of educational financing in commercial banks. Cogent Economics & Finance, 12(1), 1–17. https://doi.org/10.1080/23322039.2024.2339519

Moses, A., & Dicky, B. (2024). Bank credit and loan repayment rates during COVID-19 in Kabale District: A case of Lyamujungu SACCO. International Journal of Indonesian Business Review, 3(1), 34–50. https://doi.org/10.54099/ijibr.v3i1.703

Nsamba, L., & Tumuhaise, B. (2025). Beyond collateral: A legal analysis of the challenges and prospects of credit-worthy lending in Uganda. International Journal of Law, 11(10), 31–35.

Nugraheni, P., & Risman, A. (2025). The determinants of firm value: Commodity prices, exchange rates, inflation, and business risk as intervening variable. International Journal of Indonesian Business Review, 4(1), 76–87. https://doi.org/10.54099/ijibr.v4i1.1134

Nweke, O., & Bakare, F. A. (2025). Automated evaluation systems utilizing data science for enhanced accuracy, transparency, and decision optimization. World Journal of Advanced Research and Reviews, 25(2), 2606–2625. https://doi.org/10.30574/wjarr

Nyandoro, M., Dube, T., & Makochekanwa, A. (2023). Banking institutions survival strategies and financial policies in a challenging economy, 2007–2015. In Zimbabwe's never die? (pp. 219–253). Brill. https://doi.org/10.1163/9789004547339

Ofria, F., & Mucciardi, M. (2022). Government failures and non-performing loans in European countries: A spatial approach. Journal of Economic Studies, 49(5), 876–887. https://doi.org/10.1108/JES-01-2021-0010

Ogundele, O. S., & Nzama, L. (2025). Risk management practices and financial performance: Analysing credit and liquidity risk management and disclosures by Nigerian banks. Journal of Risk and Financial Management, 18(4). https://doi.org/10.3390/jrfm18040198

Oo, Z. M. M. (2025). Factors affecting organizational performance of Hana Microfinance [Master's thesis]. MERAL Portal.

Oppusunggu, L. S. (2022). The influence of interest rate level and non-performing loans on the performance of rural banks in Indonesia. Cuadernos de Economía, 45(128), 105–112. https://doi.org/10.32826/cude.v1i128.712

Restaino, M., & Bisogno, M. (2019). A business failure index using rank transformation. International Journal of Economics and Finance, 11(1), 56–65. https://doi.org/10.5539/ijef.v11n1p56

Rodima-Taylor, D. (2022). Platformizing Ubuntu? FinTech, inclusion, and mutual help in Africa. Journal of Cultural Economy, 15(4), 416–435. https://doi.org/10.1080/17530350.2022.2040569

Samreen, A., & Zaidi, F. B. (2012). Design and development of credit scoring model for the commercial banks of Pakistan: Forecasting creditworthiness of individual borrowers. International Journal of Business and Social Science, 3(7), 155–166.

Samreen, A., Zaidi, F. B., & Sarwar, A. (2013). Design and development of credit scoring model for the commercial banks in Pakistan: Forecasting creditworthiness of corporate borrowers. International Journal of Business and Commerce, 2(5), 1–26.

Sani, A. (2025). Effects of non-performing loans on the financial performance of selected banks on the Ghana Stock Exchange. International Journal of Research and Scientific Innovation, 12(10), 1–16. https://doi.org/10.51244/IJRSI.2025.1210000157

Saunders, M., Lewis, P., & Thornhill, A. (2016). Research methods for business students (7th ed.). Pearson Education.

Schweser, K. (2012). Schweser notes for the CFA 2013 Level 1—Book 3: Financial reporting and analysis. Kaplan.

Sekaran, U., & Bougie, R. (2009). Research methods for business: A skill building approach. John Wiley & Sons.

Selim, M. M., & Alshareef, N. (2025). Trends and opportunities in renewable energy investment in Saudi Arabia: Insights for achieving Vision 2030 and enhancing environmental sustainability. Alexandria Engineering Journal, 112, 224–234. https://doi.org/10.1016/j.aej.2024.10.107

Shi, D., Maydeu-Olivares, A., & DiStefano, C. (2018). The relationship between the standardized root mean square residual and model misspecification in factor analysis models. Multivariate Behavioral Research, 53(5), 676–694.

Sriram, H. K. (2022). Advancements in credit score analytics using deep learning and predictive modeling techniques. International Journal of Scientific Research and Modern Technology, 1(12), 1–17. https://doi.org/10.38124/ijsrmt.v1i12.453

Sumanth, C., & Sharan, K. (2024). Explainable artificial intelligence in high-stakes decision-making: A systematic review of methods, applications, and challenges. International Journal of Engineering Science & Humanities, 14(1), 123–134.

Sustersic, M., Mramor, D., & Zupan, J. (2009). Consumer credit scoring models with limited data. Expert Systems with Applications, 36(3), 4736–4744.

Swamy, V. (2015). Modelling bank asset quality and profitability: An empirical assessment (Economics Discussion Paper No. 2015-27). Kiel Institute for the World Economy. http://www.economics-ejournal.org/economics/discussionpapers/2015-27

Tavakol, M., & Wetzel, A. (2020). Factor analysis: A means for theory and instrument development in support of construct validity. International Journal of Medical Education, 11, 245–247. https://doi.org/10.5116/ijme.5f96.0f4a

Thomas, J. R., Nelson, J. K., & Silverman, S. J. (2011). Research methods in physical activity (6th ed.). Human Kinetics.

Thomas, L., Crook, J., & Edelman, D. (2017). Credit scoring and its applications (2nd ed.). SIAM.

Thompson, B. (2018). Exploratory and confirmatory factor analysis: Understanding concepts and applications. American Psychological Association.

Waweru, N. M., & Kalani, V. M. (2009). Commercial banking crises in Kenya: Causes and remedies. African Journal of Accounting, Economics, Finance and Banking Research, 3(3), 12–33.

Wolters, P. T., & Jacobs, B. P. (2019). The security of access to accounts under the PSD2. Computer Law & Security Review, 35(1), 29–41. https://doi.org/10.1016/j.clsr.2018.10.005

Worku, Z. (2021). Business ethics and the repayment of loans in small enterprises. Journal of Applied Business Research, 37(2), 1–10.

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