



Analysing the Impact of Loan Portfolio Management Models on the Performance of Commercial Banks in Zimbabwe

Fungai Tichawona Matika*, Nobubele Potwana, Sijuwade Adedayo Ogunsola*,
Bongani Innocent Dlamini

Faculty of Management Sciences, Durban University of Technology, Durban, South Africa

Email: *ftmatika@yahoo.com, nobubelep93@gmail.com, *sijuwadeo@dut.ac.za, dlamini@dut.ac.za

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Abstract

In the 1920s, the United States of America encountered unusual bank failures that had a ripple effect on other continents, including Africa and Asia. Among the African nations most severely impacted by bank collapses were Zimbabwe, Kenya, Nigeria, and South Africa. An increase in non-performing loans was the primary factor found in each case. In Zimbabwe, this issue arose following its independence in 1980 and has persisted despite multiple interventions by the Central Bank of Zimbabwe to modify lending policies. The overarching study aim is to establish how effective these loan models are in ensuring the sustainable performance of Commercial Banks. To address these concerns, the efficiency of the loan models was examined using a sequential explanatory design using a mixed-method approach. A standardized questionnaire with a 5-point Likert scale was employed for the quantitative phase of data gathering. Using a stratified sampling technique, data were gathered from 406 participants employed by 14 Commercial Banking Institutions in Zimbabwe. Using AMOS v. 24.0 and SPSS version 24.0, this collected data was examined to produce descriptive and inferential statistics. For a more thorough comprehension and explanation of the survey results, a structured interview was utilised in the qualitative phase of the research approach with both current and former chief risk officers. Structural Equation Modelling provided estimates of the strength of all hypothesised relationships, where necessary, whilst Novel was used to analyse qualitative data. The Credit Score model has been embraced by many banks, according to the statistics, while the Z-score model has been employed the least. The results revealed that a loan model's characteristics can, in certain cases, affect the model's efficacy throughout the loan cycle. There is a negative correlation between various loan models and theories of credit risk. In addition,

non-performing loans result from parameters in the loan model being inadequate; these parameters are typified by old models, unfavourable markets, insufficient cash flows, and improper use of a loan model as the bankers perceived the problem. The findings have implications for commercial banks, one of which is that loan models should be reviewed frequently to manage credit risks resulting from the present business environment.

Subject Areas

Corporate, Financial Services

Keywords

Central Bank, Commercial Banks, Credit Risk, Loan Model, Zimbabwe

1. Introduction

In recent years, the financial sector in Zimbabwe has developed, even though it has not performed well since the country adopted a multi-currency system in 2009 and did not convert the Zimbabwe dollar. A variety of factors contributing to financial reforms and/or their reversal were highlighted in studies that thoroughly examined various aspects of Zimbabwe's banking sector as a result of the financial sector's loss of confidence, the negative effects of hyperinflation, and subsequent financial reforms/reversals. It has been demonstrated that financial reforms have detrimental welfare implications, such as macroeconomic instability, even though they typically precede growth. Poor reform design and implementation have emerged during the process, underscoring the absence of donor backing and the lack of political will to see through reforms to the point that policies have reversed. This being the case, a study conducted from 2009 to 2018 on the "effectiveness of loan portfolio management models on the performance of commercial banks in Zimbabwe" found that although mishandled and ill-timed, financial reforms have the potential to trigger an economic crisis. Restructuring and transformation are nevertheless essential to the nation's growth and transformation strategy. According to the conclusions reached during this study, Zimbabwe's financial sector needs more comprehensive reforms to grow and stabilise. These reforms should include the development and implementation of a wide range of products to satisfy the needs of investors and the establishment of systems and procedures for tracking performance metrics.

The efficiency of the loan models in loan portfolio management (LPM) in Zimbabwe's commercial banks is the main topic of the study. The difficulties facing Zimbabwe's banking industry and loan quality are discussed in this paper. The suitability of the tools currently in place, including loan models (Mileris 2012) [1] is being examined in here. Loans account for the majority of Zimbabwe's financial assets, and the country's financial institutions are significantly at risk from the high rate of non-performing loans (NPLs) (Reserve Bank of

Zimbabwe 2018) [2].

Bolton *et al.* (2019) [3] emphasize the significance of efficient lending models and credit risk management, contending that banks foster economic growth in the presence of a stable financial system. Thus, certain well-known loan models that were created fifty years ago and were thought to be applicable in Zimbabwe and around the world were validated by this study. In light of the risks and difficulties the banking industry in Zimbabwe faces, this paper makes the case that banks must maintain high-quality assets through enhanced loan portfolio management, which is supported by efficient lending models. To test and understand the relationship between the key factors in the loan models, the following hypotheses were developed and tested.

H₁: The type of loan model used has an impact on loan performance.

H₂: The loan model parameter attributes used have an impact on loan performance.

H₃: Loan model effectiveness impacts loan performance.

H₄: Loan model efficiency measures impact loan performance.

H₅: Enhanced Loan Model improves loan performance.

Both regulators and financial organisations in Zimbabwe can benefit from the knowledge acquired.

2. Commercial Banks

Olalekan, Olumide and Irom (2018) [4] define Commercial Banks as national enablers and facilitate development in an economy requiring the use of reliable tools when evaluating borrowers. They conduct other commercial transactions, exchange money, take deposits, provide loans, and carry out other financial operations. They are not specifically founded with cooperative, agricultural, industrial, or any other type of purpose-specific goals in mind. In Zimbabwe, the banking sector was largely dominated by commercial banks at independence. Prominent among the banks that offer commercial banking services are the Bank of Credit and Commerce of Zimbabwe (Commercial Bank of Zimbabwe), Barclays, Grindlays (Stanbic), Rhobank, and Standard Bank, in addition to Zimbank (ZB Bank), which were largely foreign-owned (Banda 2022) [5]. These banks complement their services with merchant banks, with the majority being subsidiaries of commercial banks, such as; Standard and Syfrets, both merchant banks (Zimbank) and an independent institution, the Merchant Bank of Central Africa. These banks were founded to carry out business functions. They combine communal funds and set them aside for beneficial purposes, meeting the monetary demands of contemporary industry in the process.

The crucial role that commercial banks play in assisting the economy's operations in a variety of ways is emphasised by (Kamau, Nkaabu, and Cheronono 2023) [6]. The bank ensures:

a) Extension of Credits: Credit is being extended to deserving debtors. When it comes to funding the country's commercial, industrial, and agricultural endeavours, bank lending plays a significant role.

b) Facilities for Financing of Foreign Trade: Commercial banks facilitate overseas trade transactions through the insurance of commercial letters of credit. They also provide for foreign exchanges needed by travellers and business organisations.

c) Creating Money: A commercial bank makes and spends money following central bank directives. The ability of the commercial banking system to produce money is extremely important to the economy because it fosters the development of an elastic credit system, which is essential for economic growth.

d) Payment Mechanism: This task is carried out by commercial banks, who provide quick and easy fund transfers using credit card and cheque services.

e) Safe Custody: Banks make arrangements for the safekeeping in secure vaults of their customers' valuables, securities, jewellery, and other items.

f) Reference: When needed, they offer references regarding the financial standing of their clients. They discreetly provide this information. This is carried out when a customer requests that they connect with new businesses both domestically and abroad.

g) Agency Function: The bank represents its customers in its capacity as an agent. Payments are received by them on their behalf. They get dividends on the shares, rent, and other payments. They follow the depositors' instructions to pay insurance premiums and other bills. On behalf of their clients, they take receipt of bills of exchange. When they pay for the acquisitions of products, they give the bill of lading or railway receipts to the buyers. The suppliers of goods receive this sum. In addition to all these services, commercial banks also provide credit cards and make arrangements for the issuance of Visa international cards. Some of them give preference to lending to young people without jobs who are educated for little projects.

These banks were founded to increase the financial well-being and facilities of the populace, to lend money to business, industry, and agriculture sectors, and to provide banking services to the nation as a whole. It gives the economies of developing nations access to internal resources. Through its branches, it gathers diverse capital from across the nation (Sethi and Bhatia 2023) [7].

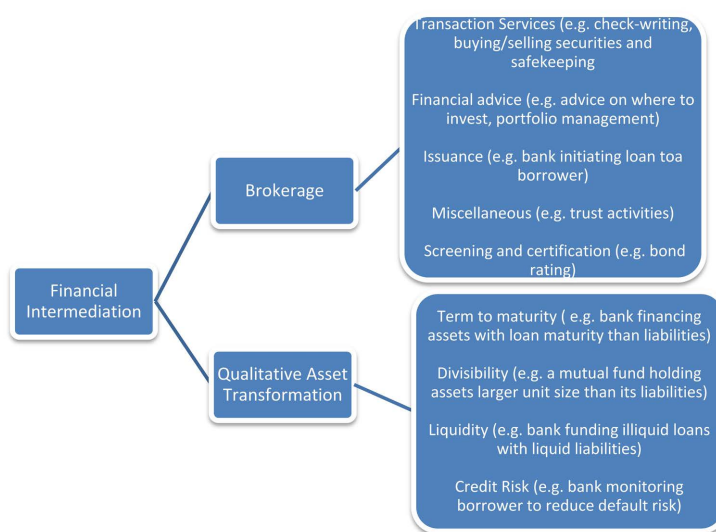
Commercial banks' operations serve as a gauge of the nation's economy. The amount and make-up of their transactions are indicative of the national economy. Through funding the needs of the nation's businesses and commerce, commercial banks have been instrumental in determining the course of economic growth over time. Banks have promoted capital building in the nation by promoting frugality among the populace. To help bring dispersed resources into the organised banking sector so they can be distributed among other economic activities, commercial banks encourage savers to retain their savings in the form of bank deposits. They contribute to the creation of the nation's capital assets. Banks facilitate economic growth by generating money, which in turn encourages community-saving and opens up new opportunities for economic expansion. The public, joint, or private sectors of any kind of organisation can obtain funds from banks, which in a planned economy enable the complete planned

productive process. As much as possible, the production plan that banks fund incorporates all of the plan's goals, including employment income distribution (Alsharari 2024) [8].

Based on diverse definitions and perspectives on commercial banking, it can be inferred that the purpose of a commercial bank is to gather dispersed funds and allocate them to economically productive sectors of the economy. Commercial banks play a crucial role in guiding the system's economic activity. Not only are the commercial and industrial activities in highly developed economies paralysed in the absence of banks, but the majority of economic activity, particularly in the organised sectors, is bank-dependent in developing economies as well. Thus, to put it succinctly, the expansion of commercial banks inside the economy is correlated with the expansion of the overall economy.

3. Conceptual Framework

The study is underpinned by the Financial Intermediation theory which was developed by Bhattacharya and Thakor (1993) [9]. It focuses primarily on commercial activities that extend brokerage services and qualitative asset transformation. Diagrammatically shown below are these trimmed activities (**Figure 1**):



Source: Bhattacharya and Thakor (1993) [9].

Figure 1. Brokerage and qualitative asset transformation diagram.

Brokerage: The method by which financial intermediaries, including commercial banks, connect savers and borrowers without altering the nature of a transaction in exchange for a commission.

Transaction Services: Commercial banks serve as financial intermediaries, facilitating simple transactions such as the purchase and sale of securities. The safekeeping of client valuables is another service that can be provided.

Financial Advice: Commercial banks advise their clients on a variety of topics, such as the assortment of investment products accessible, their returns, and

their maturity term, because they are professionals and experts in the field. Advice on diversifying a client's portfolio to lower concentration risk is also available.

Issuance: Commercial banks provide loan products to their clients; as a result, the banks initiate the entire process and issue official documents, including a loan facility letter that is signed by both parties and is admissible in court in the event of a disagreement.

Miscellaneous (trust activities): Commercial banks engage in a variety of business ventures and provide multiple goods and services. Trust actions can be accomplished, for instance, by guaranteeing that money is constantly accessible for withdrawal when customers need to access their money or investment.

Screening and Certification: To guarantee that no losses would occur, commercial banks thoroughly assess and analyse all of their offerings before completing any transaction. For instance, when evaluating a bond rating, they first analyse the bond's creditworthiness.

Qualitative Asset Transformation: This is the process of resolving and mitigating risks that are inherited in a transaction or that are mediated and processed.

Term of maturity: Commercial banks make sure that clear terms are used in all transactions involving the bank and its clients. For example, when a loan is given, it should be made clear to both parties how long it will remain in effect.

Advisability rule: This is a scenario in which a commercial bank might make investments in mutual funds, which are essentially stocks, bonds, or other trading securities. As a result, mutual funds are categorised into multiple groups based on an investor's capacity to absorb them all.

Liquidity: This means that banks draw in deposits and investments to support their loan book (funding of illiquid loans with liquid liabilities). A bank's liquidity is also enhanced via loan repayments. Commercial banks and other financial intermediaries accept short-term liquid deposits, which are used as collateral for long-term illiquid loans. This process requires both liquidity and maturity.

Credit risk: Commercial banks focus on mitigating non-payment of loans from the onset and/or during the evaluation stage because they perceive a risk that a borrower will not fulfil its commitments, resulting in a financial loss. This suggests that banks create instruments that aid in the identification of possible defaulters, such as loan models. Additionally, credit is only given to creditworthy customers, and even then, it must be watched to make sure payments are made on schedule.

The theory of financial intermediary plays a crucial role in this research because commercial banks that accept deposits gather pertinent data to enable banking activities like loan origination while also sharing a variety of risks with borrowers (Boda and Zimkova 2021) [10]. Using loan models that reduce defaults, this study focuses on creating high-quality loans. This work falls under the umbrella of financial intermediation theory because brokerage focuses spe-

cifically on the issue or origination of loans using the right tools to return quality assets. Moreover, credit risk management, especially, is the category under which the study falls. Commercial banks work very hard to guarantee that all loans made will be repaid by borrowers. To this end, they manage asymmetric information, use the best tools to assess client creditworthiness, manage risk, and perform risk transformation (Scholtens and van Wensveen 2000) [11]. All inherited risks are changed after loans are granted, controlled through risk transfer, and risk is shifted from one party to the next. Other ways to accomplish this would be buying an insurance policy, actively controlling risk that would have been assumed, and closely observing clients (Boda and Zimkova 2021) [10].

Many theorists have addressed the distinct roles of financial intermediaries, whether they are deposit-taking or non-deposit-taking organisations, which has led to a deeper analysis of financial intermediation theory. Reducing information costs, assigning responsibilities like monitoring bank facility (loan) agreements, deposit safekeeping, transaction clearing, and agency safety are a few examples of financial intermediary activities. This runs counter to the claims made by Bhattacharya and Thakor (1993) [9] regarding the topics that financial intermediation theory ought to address, including borrower resource selection, bank regulation, maturity transformation, loan allocation, and liquidity transformation. The main reason for this was their function in offering brokerage and qualitative asset transformation.

While many academics have praised the aforementioned idea of financial intermediation rules, some have pointed out flaws in the notion. For instance, transaction cost and asymmetric information were the cornerstones of classical intermediation theories, which were developed primarily to explain deposit-taking and insurance company institutions (Allen and Santomero 1997) [12]. Other criticisms include the fact that it did not take into account recent advancements in the financial sector, demonstrating the continued need for intermediation.

According to Allen and Santomero (1997) [12], financial intermediaries are now in charge of the new options markets that were previously developed between private citizens and corporations. Hence, it is essential to assess the function of financial intermediaries in light of participation costs and risk trading rather than the expense of established transactions and asymmetric knowledge. In support of this claim, Allen and Santomero (1997) [12] highlight the increasing asset shares of mutual funds and pension funds relative to the declining asset shares held by banks and insurance firms.

When it comes to the methodology to be used while developing a financial intermediation theory, Scholtens and Van Wensveen (2003) [11] agree with Allen and Santomero (1997) [12] that they mean functional methodology rather than institutional methodology. However, there are differences between these authors on the following points: Financial intermediation has always included risk management; also, one of the most notable aspects of financial intermediation is the divergence in their perspectives about participation costs. It would seem from this that other factors like risk management and knowledge asymme-

try were just as crucial. It has also been suggested that the existence of financial intermediaries is not the outcome of an imperfect market, but rather that there is a need to identify savers and borrowers require an intermediary.

The same views were expressed by Scholtens and Van Wensveen (2003) [11] on the importance of risk identification and mitigation as focal transactions. Comparably, risk management may be seen as the foundation of insurance, starting with the process of banks managing and transforming risk. This is seen in the exports made by several Italian insurance businesses and merchant banks. Their claims, which are based on the fact that investments and loans are linked to many hazards, including interest rate, liquidity, and credit risks, emphasise how crucial it is for banks to reduce all of these risks, particularly when it comes to new markets and products offered in diverse parts of the world.

In the Scholtens and Van Wensveen (2003) [11] model, risk management is positioned at the centre of intermediation. Risks that are addressed include maturity, market (interest and stock price), counterparty, life, and income expectancy risk, among others. Financial organisations employ their reputation, balance sheet and off-balance sheet items, instead of their limited resources, to function as counterparts. In actuality, financial institutions are among the most leveraged businesses of all types of private enterprises because of their equity in depositor liabilities. Although they did not agree, Brei, Borio, and Gambacorta (2020) [13] discovered that other variables, rather than financial intermediation, were responsible for Nigeria's economic growth.

Though there have been criticisms of the notion of financial intermediation, it is crucial to remember that financial intermediaries both reduce risk and add value to the economy. Credit risk management, which attempts to lower default rates and raise loan quality, is also the main emphasis of this study. Consequently, banks possess the ability to mobilise resources, extend credit to their clients, and, if necessary, facilitate transactions through syndicating, which is pooling resources from multiple banks to raise a significant sum for a project with economic value. Therefore, for the following reasons, financial intermediation theory is relevant to our study: Banks that deal with savings and loans in particular take on risks associated with every transaction involving these parties. In carrying out their operations, banks frequently run the danger of interest rate fluctuations, liquidity problems, credit issues, and operational hazards. The study's primary risk is credit risk mitigation, which is related to the likelihood of borrower default. As a result, a commercial bank must have strong credit practices, such as loan models that allow the bank to separate prospective bad borrowers from those who have the potential to make payments.

4. Loan Portfolio Management

Loan Portfolio Management (LPM) describes the procedure used to monitor and regulate the risks involved in granting credit. It is a straightforward method of examining systems, coupled with the procedures and policies that determine portfolio quality and address the real portfolio sample, which is distributed

throughout financial institution branches. It can be used by banks for loan portfolio assessment (Abdus 2004) [14]. Gregoriou and Hoppe (2009) [15] describe LPM as methodically giving a loan portfolio meticulous attention, including assessing the risk or return profile of the portfolio and strengthening its soundness and lowering default rates Geek (2014) [16], through monitoring. In addition to highlighting systemic shortcomings, a comparison of the current portfolio management system to internationally recognised organisational guidelines and best practices also reveals ineffective controls and the associated risks in the processes. This makes risk, return, and monitoring to be the three primary LPM elements.

4.1. Risk

Risk is the inability to produce anticipated results which hinder business. Foreign exchange, commodity, nation, and market risks are a few of the hazards connected to LPM, along with settlement, concentration, and systemic risks. When an investment or the profits on it are negatively impacted by an unstable exchange rate, this is known as foreign exchange risk (Madeira 2018) [17]. When an investment or the profits thereon are negatively impacted by an unstable exchange rate, this is known as foreign exchange risk (Madeira 2018) [17]. In this paper we contend that since all investments are vulnerable, it is necessary to implement mediatory methods to unravel the risks that are inherited at loan inception or during loan lifetime. For instance, in Zimbabwe, a client may apply for a loan in ZAR, but the bank will record losses when other multi-currency begins to firm up, as the currency begins to lose value. Consequently, one may claim that the described risk plays a significant role in portfolio management since it puts the borrower in danger of difficulties and non-performing loans (NPLs) if they employ a lower currency to satisfy their obligation.

Poitras (2015) [18] views commodity risk as the result of the interaction between business uncertainty and commodity price volatility. The primary drawback of this risk is that when prices decline, meaning that a borrowing client who had previously purchased the good at a higher price is unable to recoup expenses and, as a result, is unable to fulfil the loan obligation, leading to non-performing loans (NPLs) in the portfolio.

Els *et al.* (2010) [19] identify country or nation risk as a political risk and Khaled and Wahab (2019) [20] advise that investors should consider the current political climate and economic performance. These are essential for favourable cash flows that support debt servicing and high production levels. This risk affects the bank's loan portfolio since a bad political climate might interfere with a company's ability to operate smoothly, which can lead to NPLs. One could argue that it is necessary to lessen exposure to certain businesses that are significantly impacted by politics and focus on others that are more moderate, like the retail industry, as people still need to purchase staple foods during times of conflict.

Market risk includes financial losses resulting from fluctuations in the pricing of different instruments (Szylar 2014) [21]. Market risk also includes additional

price signals with values derived from the public market, as well as losses incurred by bank traders as a result of changes in equity, interest rate, credit spread, and foreign exchange rate fluctuations. We thus postulate that is critical to implement mitigation strategies since any loss will negatively impact the portfolio's performance.

Settlement risk, according to Garp (2007) [22], is the loss that arises from the counterparty's failure to fulfil or pay off the borrowings by the deadline. According to Khaled and Wahab (2019) [20], this risk materialises as soon as the money is released to the other party; an example of this would be banks' lending money to one another or providing overnight accommodations to bridge a day's difference. This paper makes the case that counterparties must be given proper restrictions after receiving a thorough review of their clients, as their noncompliance will negatively affect the lender's liquidity position and bank loan portfolio.

Concentration risk occurs when funds are given to a single client or when an institution's portfolio is biased towards particular industries (Bolder 2018) [23]. Thus, focused lending to a single industry or client exposes the bank to unfavourable events that affect debt repayment. Consequently, it is critical to mitigate this risk, which has a detrimental effect on a loan portfolio.

Madeira (2018) [17] posits that systemic risk is the result of market forces acting upon major market participants, causing a deceleration in the flow of banking transactions. Political turmoil like large-scale protests is a common source of this kind of risk since it can disrupt the business operations of certain borrowing clients, making it more difficult for cash flows to settle loans. If systemic problems continue, a portfolio cannot perform well, necessitating the need for money to bridge a liquidity gap or a buffer position.

4.2. Return

The rate of return highlights and illustrates the benefits of a project that is motivated by cash flows rather than by rates that are offered elsewhere (Firer *et al.* 2012) [24]. The projected return rate by the investor is also known as the minimum permissible rate of return, and it should be at least as high as the bank's investment return. Additionally, a strong return shows a likelihood of loan performance, which lowers the number of non-performing loans in a mix.

Marx *et al.* (2017) [25] define return as the entire advantage or disadvantage of an asset over a certain time frame. The benefit is realised when an asset provides the bank with extra cash flows. It can be calculated yearly as a percentage using the following formula:

$$R = \frac{P_{t-1} + C_t * 100}{P_{t-1}}$$

where P_t is the asset's price (value) at period t , P_{t-1} is the asset's real price (value) at period $t - 1$, and R is the yearly return; The net cash inflow from the asset from $t - 1$ to t is represented by C_t Marx *et al.* (2017) [25].

4.3. Monitoring

Gregoriou and Hoppe (2009) [15] describe monitoring as the process of keeping a relationship with the client and assessing its performance and likelihood of making repayments as agreed. Saleh, Alkasasbeh and Bader (2017) [26] posit that one of the tools used for monitoring client performance is through models that also employ information obtained from clients' financial statements to determine future bankruptcy. These financial statements could be a statement of financial position that records the way company monies were utilised in assets and outstanding liabilities and the build-up of company capital or equity during the period under review; a comprehensive income statement that reveals income generated during a financial period and may indicate potential future performance of a company, should the company maintain a certain trend; a cash flow statement presenting company capacity to generate sufficient cash or surplus cash, which enables the borrower to maintain its going concern status and service commitments.

To fully value company performance, the lender must perform ratio analysis, a statistical indicator expressed mathematically by relating key financial information (Megginson, Smart and Lucey 2008) [27]. Ratio analysis requires statistical computing and interpreting the numerical relationship between two items based on available financial statements and the relationship. Profitability, solvency, and liquidity ratios are the most used ratios.

Profitability ratios, which are gross profit margins and net profit margins, measure a company's success and are used to determine bonus payments (Gregoriou and Hoppe 2009) [15].

Solvency is described as a situation whereby sufficient resources exist to meet debts when due (Wood and Sangster 2005) [28], therefore, solvency ratios show a company's obligations against its size. The debt Ratio calculated as Total Debt/Total Assets is an example of a solvency ratio. The debt ratio demonstrates the debt funding levels being used by a company to fund its operations.

Liquidity ratios determine a company's capacity to meet short-term obligations (Megginson, Smart and Lucey 2008) [27]. Examples are the Current ratio-calculated as Current assets/Current liabilities. The standard acceptable ratio is 2:1, showing how many times current assets may expunge current liabilities. The bank is unlikely to be interested in extending credit to an entity that cannot use current assets to pay its liabilities. Then there is the Acid Test/Quick Ratio, calculated as Current Assets-Stocks/Current Liabilities, or the extent to which a company may pay its short-term liabilities without necessarily selling some of its stock. This demonstrates the company's liquidity levels or cash surplus, which may accommodate additional borrowings. All the ratios obtained are weighed in the model to contribute towards the final model score.

Megginson, Smart and Lucey (2008) [27] have, however, raised concerns regarding ratios, as far as the existence of a possibility that a firm's inconsistent adherence to one accounting policy may distort the trend, as there might be

situations in which ratios may only be used when comparing two different time-frames, hence ratios are not applicable in a company's first year of trading.

According to Rose and Hudgins (2010) [29], the bank also applies loan reviews and workouts to achieve sustainable LPM, with the process of identifying difficult clients who are not performing in line with contract terms referred to as a loan review, whilst a workout is the rehabilitation of bad debts. Loan models are also used to achieve this objective. Furthermore, the loan review process validates compliance and conformity of loans granted against a bank's loan policy, while employed by active bank management as a quality control instrument to monitor the quality of an established loan portfolio and new lending activity.

It is essential to undertake a loan review for the following reasons: to evaluate adequacy and adherence to the bank's policy and processes, as well as that of the regulator; for management to objectively assess loan quality; to identify loan performance trends and to identify missing loan documents, as well as unsecured loans (Rose and Hudgins 2010) [29]. Additionally, management of a loan portfolio is essential as it leads to the safety of an institution due to quality loans making it imperative for a bank to have a skilled team management of the clients. Successful management of clients demonstrates the effectiveness of the loan model.

5. Methods

A descriptive research design was believed to be most appropriate for this mixed methods study as it describes the features of constructs and supplies information on what has been uncovered about the event or the organization. Data was collected from 406 individuals who worked for 14 commercial banking institutions in Zimbabwe using a stratified sampling technique. The captured data was analysed in SPSS version 24.0 and Analysis of Moment Structures (AMOS), to yield descriptive and inferential statistics. The use of a questionnaire is advantageous in that it is cheaper and quick to administer, in addition to an absence of interviewer bias, and it offers convenience for respondents. There is a downside though, with respondents possibly not agreeable to answering specific questions or in fear of providing incorrect answers should they encounter questions not properly worded. Respondents may even have a biased attitude, which can then result in misleading results (Saunders, Lewis and Thornhill 2012) [30]. However, in a bid to circumvent this, a 5-point Likert scale was used on the questionnaire, which is the most suitable tool to measure attitudes (Walliman 2021) [31]. The preference of a 5-point Likert scale was based on the advice of Walliman (2021) [31], who maintain it gives the respondent an option of choice without stress.

A non-probability sampling technique, purposive sampling, was employed to collect qualitative data through interviews. Purposive sampling mitigates the random selection of participants but strategically selects sampled participants who are key, relevant, and able to respond to questions sought by the study (Bell,

Bryman and Harley 2018) [32]. In this study, only risk specialists were considered as the most appropriate participants in the qualitative phase, because of their skills in managing credit risks that impact LPM. This approach resonates with Creswell and Creswell (2018) [33], who posits that judgement by the researcher plays a key role in selecting the most appropriate participants. In addition, Fellows and Liu (2021) [34] concur. A total of 29 participants were interviewed from each bank, 14 of whom were risk officers from existing banks, while the 15 was from failed banks. The sample was guided by recommendations from Teddlie and Tashakkori (2009) [35], who argue that any number ranging between six and 29 is sufficient or a good representative number of participants for interviewing in a study.

Interviews conducted were face-to-face and semi-structured, with a comprehensive interview guide that facilitated the smooth conduct of the interviews and, subsequently, data collection. To obtain the most appropriate data, the interview guide was intensely evaluated by experts in the banking sector to ensure no information was omitted that could not be obtained with the quantitative questionnaire. All coding and analysis of participant responses were achieved through NVivo software. According to Sreejesh (2014) [36], the NVivo software offers a system that can fully analyse qualitative data, as it can bring to the fore, shape and make sense of unstructured information. Furthermore, many manual tasks were reduced, thus allowing much-needed time to discover tendencies as well as recognise themes (McNabb 2017) [37]. Cronbach's alpha was used to evaluate the measuring items' internal consistency and content validity and made sure the questionnaire was pretested and examined with two academics' help. Factor loadings were used to measure convergence; factor loadings more than 0.5, but ideally over 0.7, indicated that the indicators were converging on the same latent factor (Sekaran and Bougie 2009) [38].

6. Results and Discussion

This section captures the key findings of the study, obtained from both the quantitative and qualitative analysis of responses from the study sample. This is done in line with each research objective.

Research objective one.

The first research objective sought to establish whether LPMMs exist and are applied in Commercial Banks in Zimbabwe.

The results (Table 1) show that of the four types of LPMMs, three were rated above the midpoint. The most common was the Internal Credit Score Model ($M = 4.22$; $SD = 0.780$), which had the highest positive kurtosis statistic of $K = 1.501$. The second highest rated was the Asset-Based model ($M = 3.65$; $SD = 0.721$), with a low standard deviation and a positive kurtosis ($K = 0.940$), suggesting respondents were coherent in their responses. The third highest was the use of various models on different loan products ($M = 3.31$; $SD = 1.031$). The least used type of model was the Z-Score model ($M = 2.63$; $SD = 0.930$) and because the

mean rating was less than 3.0, this meant respondents largely disagreed with using this model, indicating very limited use in the Commercial Banks. It can, therefore, be argued that more than one model is currently being used by Zimbabwe commercial banks. This puts to bed some assumptions that the NPLs were caused by a lack of lending tools used by the banks.

Table 1. Type of loan portfolio model.

	N	Mean	SD	Skewness	Kurtosis
Z-Score Model	406	2.63	0.930	0.718	-0.128
Asset-Based Model	406	3.65	0.721	-0.706	0.940
Internal Credit Score Model	406	4.22	0.780	-1.104	1.501
Various models on different loan products	406	3.31	1.031	-0.256	-0.663

Quantitative results: The quantitative results endorsed the use of loan models in Zimbabwe, with among these, the internal credit score model, Asset-based model and Z-score model. Furthermore, the internal credit score model has proceeded to be more dominant, in contrast with internationally developed models such as the Z-Score model, suggesting that it is the most appropriate loan model, which can be optimistically and objectively used in the prevailing local business environment. Another noteworthy finding from the study is that a multivariate formula is applied in the loan models. From the analysis of the findings, it is also evident ratios were not the main variable in loan models. Therefore, the study argued loan models can be distinguished by analysing the formulas they apply. In addition, this suggests the formula exhibits the strength of the loan model's prediction.

Qualitative results: Key informants concurred that internationally developed loan models such as the Z-Score, 5 Score Model, Zmijewski Probit Score, and Ohlson O-Score, as well as the Odom and Sharda 1990 models, were not favoured by Zimbabwean banks, indicating that these models could not adequately serve their purpose or fully guide banks in selecting creditworthy clients. Manufacturing is the main sector where the model was being used, followed by the mining sector. The results do show that, on the one hand, among operational banks, the accuracy rates of the loan models, en masse, were generally high being rated above 50 percent accuracy, while for the closed banks, these accuracy rates were generally lower than 50 percent. On the other hand, banks determine loan model efficiency using NPL levels.

Following the review of both quantitative and qualitative results, it can be argued that commercial banks are adhering to international best practices of employing scientifically proven tools to evaluate loan applications, as postulated by (Abdou and Pointon 2011) [39]. It can be further argued that the novel approach in this paper is needed or emphasis for the best loan model with variables skewed towards country risk, macro-economic fundamentals, and climate

change that impact businesses daily. The paper also argues that the Internal Credit score is the most suitable model in a perpetually volatile environment, as the bank can easily tailor-make it to suit the prevailing environment. The study has closed the existing knowledge gap on the loan model best suited for a developing nation with an unstable macro environment, such as Zimbabwe, in addition to types of lending tools (loan models) that lead to and facilitate LPM soundness in Zimbabwe's Commercial Banks. Therefore, it is expected bank management will, in future, vigorously examine their loan models and ensure the outlook will protect Commercial Banks' assets and preserve shareholder interest.

Research objective two.

The second research objective sought to examine the LPMM parameter attributes currently used by Commercial Banks in Zimbabwe. Additionally, the results answered the study's main research question and sub-research question; "Which parameter attributes do the commercial banks in Zimbabwe consider in LPMmodel development?" To address this research objective, two statistical approaches were utilised. First, descriptive statistics were computed and presented using the measures of central tendency (mean statistics), as well as the measures of dispersion (standard deviation). Second, dimension reduction techniques were then applied, to establish the principal factors that emerged from the model parameters.

Descriptive Statistics

The summary statistics (**Table 2**) used for the model parameter rating are presented below.

Table 2. Summary statistics.

	N	Mean	SD	Skew	Kurt
The bank uses Industry based parameters	406	3.89	0.686	-1.094	3.309
Past loan performance experienced is considered in setting parameters	406	3.96	0.645	-1.131	3.490
Parameters are author based initiated by bank or consultant	406	3.49	0.851	-0.203	-0.623
The model can incorporate sizeable factors such as financial/behavioural	406	3.85	0.572	-0.634	1.986
The outcome probabilities of the model are pre-defined	406	3.71	0.786	-0.781	0.433
A model's output can be ranked	406	4.03	0.616	-0.722	2.110
The model's benchmark is well-defined	406	3.32	1.068	-0.129	-1.114
The model is robust and has not been reviewed or replaced	406	3.50	0.976	-0.458	-0.728

The ratings were based on a 5-point Likert scale and the findings show all ratings are above the 3.0 midpoint. This suggests model parameters used were all rated positively, which meant all were being utilised often. The most dominant

attribute was the ability to rank the model outcome ($M = 4.03$; $SD = 0.616$), which was done often to ensure the comparability of various model outcomes. The second dominant attribute was the consideration of experience ($M = 3.96$; $SD = 0.645$), while the use of industry-based parameters was ranked third ($M = 3.89$; $SD = 0.686$). The ability of the model to incorporate sizeable factors was ranked fourth ($M = 3.85$; $SD = 0.572$).

The least-rated item was the model's benchmark, which was well-defined ($M = 3.32$; $SD = 1.068$). This showed the attributes having more deficiencies regarding model benchmarks, with a very high variability in responses, as observed from the exceedingly high standard deviation, as well as the significantly high magnitude of the negative kurtosis ($Kurt = -1.114$); an indication of a platykurtic distribution. The second least-rated item related to model parameters was initiated by a bank or consultant ($M = 3.49$; $SD = 0.851$) and again had a platykurtic distribution ($Kurt = -0.623$). The third least rated was that the model was robust and was not reviewed ($M = 3.50$; $SD = 0.976$); the third and last item with a platykurtic distribution ($Kurt = -0.728$). The rest of the items had a positive kurtosis, indicative that respondents had a high degree of coherence in their responses.

Quantitative results: The key findings from the study are that banks do not arbitrarily create loan model parameters, but are backed by several attributes, among them being industry-based and experienced past loan performance. The results also reveal the LMPA under use by banks are all rated positively, suggesting their influence on loan model performance. For example, items related to these attributes are on the back of outcome probabilities, robustness, and model outputs, as well as the model being able to incorporate sizeable factors, such as financial and behavioural characteristics.

Qualitative results: The five key characteristics of an effective loan model comprise a model that can capture unexpected losses; allows for ranking; is industry-based, with clear benchmarks, as well as a model that can predict future performance with accuracy. In this work, the accuracy of the loan model is regarded as key.

For the loan model, the findings mean that banks should not only be guided by their internal policies but also by monetary policies as detected by monetary authorities on risk mitigation measures, such as risk grading or rating in line with international banking standards, as demonstrated using industry-based parameters as well as experience. It can, therefore, be conclusively stated that loan model performance is a function of parameters, making it imperative to have some fundamentals in place or a basis with the main aim of targeting better accuracy on loan performance prediction, before setting these up. It can also be argued from the study that one weak parameter or misalignment of parameters can be a precursor to loan model performance, as evidenced by both NPLs and outdated loan models. In addition, internal sources such as credit policies and records on loan performance can support benchmarking of parameters, as evidenced by past loan performance experienced. The study has thus reduced the

knowledge gap created by insufficient literature addressing loan model effectiveness, given the influence of parameters.

Research objective three.

The third research objective aimed to analyse LPMM effectiveness as well as Loan performance in Commercial Banks in Zimbabwe. To achieve this, the first question put to respondents required them 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 mid-point. The summary statistics for the eight items are given below (**Table 3**).

Table 3. Summary statistics.

	N	Mean	SD	Skewness	Kurtosis
To identify good clients	406	4.00	0.773	-1.040	1.904
To ensure security adequacy	406	3.79	0.945	-0.800	0.002
To determine the regular review of security	406	3.43	0.874	-0.051	-0.615
To guide measures to be taken when a loan is in doubt	406	3.33	0.868	-0.135	-0.460
To guide assessment of sister companies of a borrowing corporate client	406	3.36	0.845	-0.088	-0.135
To determine non-performing loans	406	3.67	0.880	-0.658	-0.094
To compare performing loans to the total loan book	406	4.13	0.742	-1.313	3.610
To predict bankruptcy	406	3.63	0.876	-0.869	-0.021
Valid N (listwise)	406				

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 loanbook”, 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 statistic 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 least 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.

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 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, therefore, 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.

Quantitative results: Concerning loan model effectiveness, it was established that for a loan model to be considered effective, it should be able to select only bankable projects or creditworthy clients and ensure security adequacy (active measure). Furthermore, the study argues 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’s products, the use of outdated models, and insufficient cashflows.

Qualitative results: The major factors that affected LPM model effectiveness were the external environment; economic, social and political were top of the list. Other environments such as legal, internal, as well as technological environments were also indicated and are in line with postulations from (Reece 2010) [39]. In this study, external challenges overtake events of loan models, for example, high inflation depletes company revenues, hence, reducing 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 loan model outcomes, resultant overriding negative scores showing a potential defaulter(s).

From the findings, we argue 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. This paper also shows unforeseen circumstances, undetectable by loan models, such as social and political changes that upset loan models; hence, banks may need to be prudent and discount the scores obtained by the client at the evaluation stage. Thus, this work has narrowed down the knowledge gap on the practicality of loan models or the effectiveness of loan models found many years ago in a stable environment.

Research objective four.

The fourth research objective sought to test the influence of LPMM on loan performance in Commercial Banks in Zimbabwe. This entailed the need to test the influence of each of the independent variables on the dependent variables. Furthermore, the fourth objective sought to model the key factors influencing loan performance and establish whether the factors had a significant impact statistically.

While the variables could have been tested separately per the advice of Field (2022) [40], the independent variables often have relationships among them-

selves and testing the relationships separately does not take cognisance of the influence of other variables making separate tests flawed. In this regard, all the variables were tested holistically in a single SEM, as this allowed the model to take the effect of each independent variable on the other into account before generating the discriminant validity results. More importantly, Marlow (2023) [41] further argues that tests done separately are not comparable, whereas testing the relationships in a single model facilitates the ease of comparing the relative effect of each variable on the discriminant validity. Based on these arguments, the fourth research objective was tested using a single SEM.

According to Raju and Prabhu (2019) [42], it is imperative to first validate these constructs before modelling and this could be done using both CFA, as well as Reliability Analysis. The CFA results presented earlier showed the constructs used were valid. In confirming the validity and reliability of research constructs using CFA, the research hypotheses were then tested. Since the research comprised latent variables that were measured, each research construct was tested for several items, use of SEM was considered the most robust approach, instead of multiple linear regression techniques.

According to Sabah (2023) [43], there are two major types of SEM namely, Covariance-based SEM (CB-SEM) and Variance-based SEM (VB-SEM). CB-SEM is a parametric approach to SEM and its use is premised on data being normally distributed. VB-SEM is a non-parametric approach, and its use is not premised on the normality assumption. Since the study involved multiple constructs, multivariate normality was carried out and from the findings, the normality assumption was not violated. Furthermore, Brown (2015) [44] argued that preference for CB-SEM over VB-SEM also considers the sample size; with samples greater than 200 being ideal for CB-SEM, while samples less than 200 are best handled with VB-SEM. The final sample size used in this study was 406 and as this amounts to more than 200, CB-SEM was optimal for analysis of the hypotheses utilizing IBM SPSS Amos V26. The hypotheses tested are listed below.

H₁: The type of Loan Portfolio Management Model used impacts loan performance.

H₂: Loan Portfolio Management Model parameter attributes used impact loan performance.

H₃: Loan Portfolio Management Model effectiveness impacts loan performance.

H₄: Loan Portfolio Management Model efficiency measures impact loan performance.

The SEM model outcome is presented (**Figure 2**) below.

The latent independent variables are depicted in oval shape and the constituent items are represented by rectangles, while the error terms are represented by circles (**Figure 2**) as advised by (Kline 2023) [45]. The corresponding coefficients from the latent variables pointing in the direction of LP, are presented (**Table 4**) below.

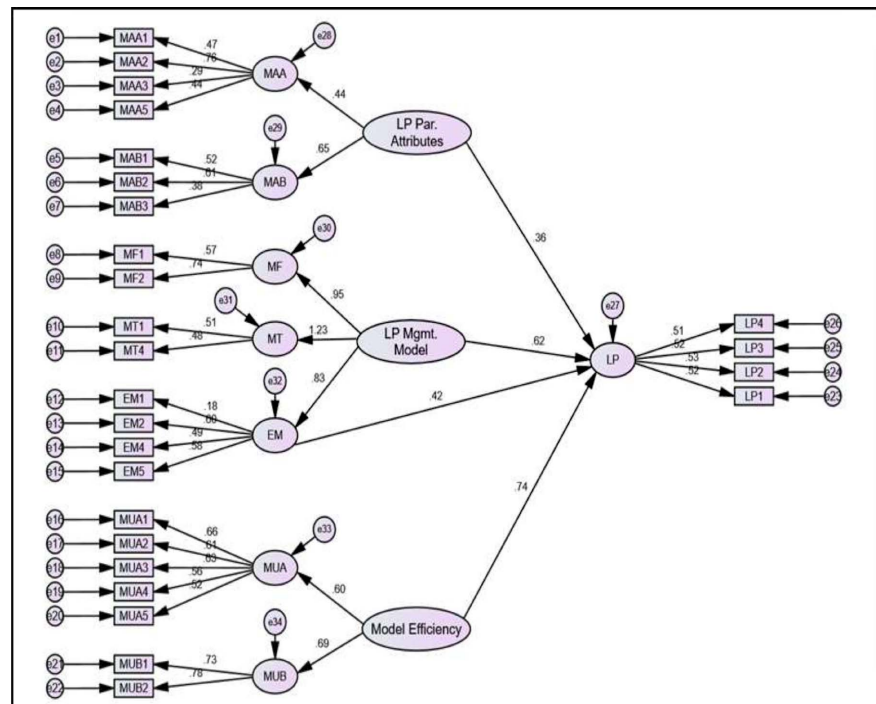


Figure 2. Structural equation model (SEM).

Table 4. Structural equation model-coefficients.

			Estimate	Standardised	S.E.	C.R.	P
EM	←	LPMM	1.000	0.830			
LP	←	LPMA	0.603	0.357	0.316	1.988	0.046
LP	←	LPMM	2.038	0.616	0.982	2.075	0.038
LP	←	LME	0.654	0.736	0.146	4.479	***
MUB	←	LME	1.000	0.687			
MUA	←	LME	0.796	0.601	0.165	4.832	***
MT	←	LPMM	4.992	1.231	1.652	3.022	0.003
MF	←	LPMM	4.754	0.946	1.591	2.987	0.003
MAB	←	LPMA	1.000	0.651			
MAA	←	LPMA	0.978	0.444	0.539	1.813	0.070
LP	←	EM	1.153	0.420	0.761	2.915	0.003

$R^2 = 0.796$.

The results show that for the relationship between loan model effectiveness (LME) and loan performance (LP), $\beta = 0.736$ ($p = 0.000 < 0.05$). For the relationship between the LPMM and LP, $\beta = 0.616$ ($p = 0.038 < 0.05$). Third, for the relationship between the Loan Portfolio Management Model parameter attributes (LPMA) and loan performance, $\beta = 0.357$ ($p = 0.046 < 0.05$). Last, for the relationship between LPMM efficiency measures (EM) and loan performance, β

= 0.420 ($p = 0.003 < 0.05$). Considering the foregoing, since the p -values were less than 0.05, the study rejects the null hypothesis for all four hypotheses and concludes with the alternative hypothesis that LPMM effectiveness, LPMM, LPMA and LPMM efficiency measures had a statistically significant relationship with loan performance.

Furthermore, of these four, the highest coefficient was for LPMM effectiveness ($\beta = 0.736$); this shows that of the four predictors, LPMM effectiveness explained the greatest variance in loan performance. On aggregate, the overall r -square was 0.796, which shows that 79.6 percent of the variability in loan performance was explained by all four predictors.

The above outcome shows the relative Chi-square was $CMIN/DF = 2.679$, which is below the maximum threshold of 3.0 (Sheard 2018) [46]. In addition, the Normed Fit Index was $NFI = 0.908$ for the baseline comparisons, whereas the Comparative Fit Index was $CFI = 0.925$, with both greater than 0.90, the minimum prescribed (Sheard 2018) [46]. Concerning the parsimony-adjusted measures, the Parsimonious Normed Fit Index was $PNFI = 0.750$ and the Parsimonious Comparative Fit Index was $PCFI = 0.792$, thus both measures exceeded the prescribed 0.50 minimum (Rosak-Szyrocka and Tiwari 2023) [47]. Last, the Root Mean Square Error of Approximation was $RMSEA = 0.072$, thus, less than 0.08, which is the maximum prescribed (Brase and Brase 2021) [48]. Therefore, as all the Goodness-of-Fit tests fall within the thresholds expected, the SEM would have a very good fit. This means the model can be considered consistent with the empirical data. These good model fit indices demonstrate the validity of the empirical model proposed in this study.

This work has thus shown that the independent variables influence loan models, hence, influencing the evaluation of potential clients, whilst dropping uncreditworthy clients, which closes the gap on the key variables argument. Therefore, the study has fully addressed both the main research and sub-research question on whether a loan model can distinguish a good client from a bad client at the onset.

Quantitative results: The findings support all the established hypotheses, demonstrating a positive relationship between key variables of loan models, that is; type of model (LPMM); parameter attributes (LPMA); model efficiency (EM) and loan performance. The results essentially exhibit that loan model effectiveness is not a function of one variable, but a combination of variables applied and weighted appropriately. Meanwhile, qualitative results reveal prevalent causes of bank failures in Zimbabwe are corporate governance issues, the use of outdated models, the lack of disaster recovery mechanisms and management complacency, as well as poor planning and poor markets.

The statistical analysis has revealed a sizeable number of variables will strengthen the performance of a loan model, suggesting a few variables may miss some risk categories. Owing to the uncertainty of the business environment, as shown by the study, it can be argued the banks should ensure the loan models are reviewed and updated consistently, as the use of defunct models causes un-

informed decisions, resulting in default risk to the banks, impacting loan portfolios. The study findings enhance the literature on loan model effectiveness, worth mentioning how the model may remain relevant to the user. Notwithstanding issues such as corporate governance, which have caused bank failures, weak loan models have also been proven a major cause of bank failures in Zimbabwe.

Research objective five.

The fifth research objective sought to identify circumstances that motivate Commercial Banks to enhance their LPMMs, leading to the development of their model and to confirm whether an LPMM impacts loan performance.

To achieve this, the independent variable, the LPMM, was considered a latent variable comprised of all the preceding independent variables. The dependent variable was loan performance. Since the variables involved were latent variables, SEM was again carried out. The corresponding SEM model is illustrated (Figure 3) below.

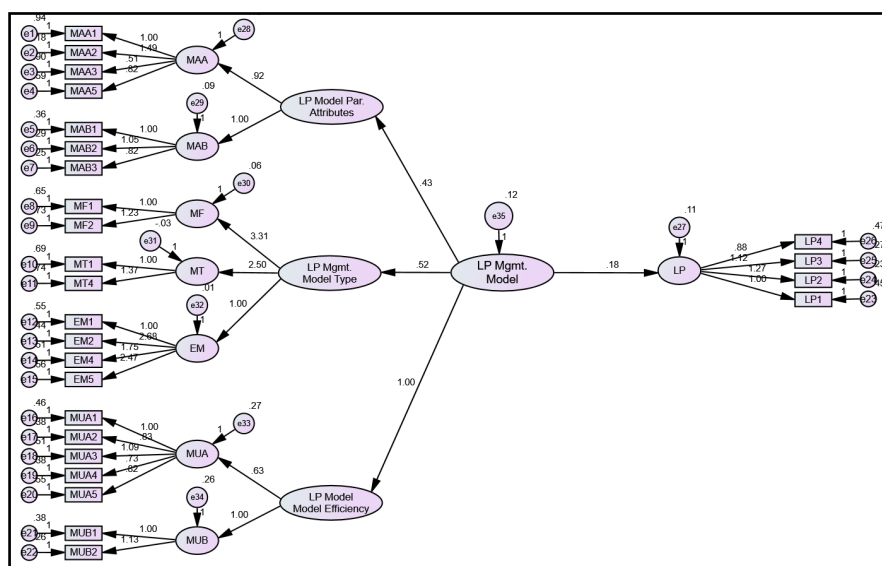


Figure 3. Structural equation model (overall dimensions).

The results (Tables 5-7) show that for the relationship between the overall latent variable LPMM and LP, $\beta = 0.183$ ($p = 0.016 < 0.05$). Since the p-value was less than 0.05, the null hypothesis was rejected. It can, therefore, be concluded that a statistically significant positive relationship exists between LPMM and LP.

The outcome shows the relative chi-square, at $CMIN/DF = 2.499$, was lower than the maximum threshold of 3.0. The Normed Fit Index was $NFI = 0.907$ for the baseline comparisons, while the Comparative Fit Index was $CFI = 0.946$, with both greater than 0.90, which is the minimum prescribed (Hair, Hult and Ringle 2014) [49]. For the parsimony-adjusted measures, the Parsimonious Normed Fit Index was $PNFI = 0.747$ and the Parsimonious Comparative Fit Index was $PCFI = 0.789$ and both measures were greater than the 0.50 prescribed minimum. Last, the

Root Mean Square Error of Approximation was RMSEA = 0.052, which was less than the 0.08 maximum prescribed (Brase and Brase 2021) [48].

Table 5. Model fit results.

CMIN	NPAR	CMIN	DF	P	CMIN/DF
Default model	63	742.643	288	0.000	2.679
Saturated model	351	0.000	0		
Independence model	26	3050.400	325	0.000	9.386
Baseline Comparisons	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.908	0.844	0.916	0.917	0.925
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000
RMSEA	RMSEA	LO 90	HI 90	PCLOSE	
Default model	0.072	0.067	0.077	0.000	
Independence model	0.144	0.139	0.149	0.000	
Parsimony Measures	PRATIO	PNFI	PCFI		
Default model	0.886	0.750	0.792		
Saturated model	0.000	0.000	0.000		
Independence model	1.000	0.000	0.000		

Table 6. Structural equation model-coefficients.

			Estimate	Standardised	S0.E0.	C.R.	P
LPMU	←	LPMM	1.000	1.000			
LPMMT	←	LPMM	0.521	1.000	0.135	3.866	***
LPMA	←	LPMM	0.429	1.000	0.108	3.960	***
MUB	←	LPMU	1.000	0.556			
MUA	←	LPMU	0.632	0.386	0.139	4.539	***
EM	←	LPMMT	1.000	0.893			
MT	←	LPMMT	2.496	1.073	0.616	4.052	***
MF	←	LPMMT	3.315	0.927	0.790	4.198	***
MAB	←	LPMA	1.000	0.446			
MAA	←	LPMA	0.922	0.306	0.318	2.896	0.004
LP	←	LPMM	0.183	0.187	0.076	2.400	0.016
MAA1	←	MAA	1.000	0.416			
MAA2	←	MAA	1.494	0.846	0.299	4.996	***
MAA3	←	MAA	0.514	0.234	0.139	3.700	***
MAA5	←	MAA	0.821	0.429	0.145	5.653	***

Continued

MAB1	←	MAB	1.000	0.482			
MAB2	←	MAB	1.049	0.538	0.221	4.745	***
MAB3	←	MAB	0.816	0.472	0.174	4.701	***
MF1	←	MF	1.000	0.621			
MF2	←	MF	1.235	0.679	0.131	9.430	***
MT1	←	MT	1.000	0.449			
MT4	←	MT	1.366	0.552	0.186	7.326	***
EM1	←	EM	1.000	0.262			
EM2	←	EM	2.680	0.629	0.616	4.348	***
EM4	←	EM	1.747	0.439	0.433	4.036	***
EM5	←	EM	2.471	0.551	0.581	4.256	***
MUA1	←	MUA	1.000	0.641			
MUA2	←	MUA	0.833	0.607	0.093	8.999	***
MUA3	←	MUA	1.089	0.650	0.116	9.363	***
MUA4	←	MUA	0.730	0.555	0.086	8.462	***
MUA5	←	MUA	0.819	0.528	0.101	8.145	***
MUB1	←	MUB	1.000	0.708			
MUB2	←	MUB	1.133	0.808	0.144	7.892	***
LP1	←	LP	1.000	0.448			
LP2	←	LP	1.275	0.670	0.216	5.901	***
LP3	←	LP	1.119	0.587	0.188	5.954	***
LP4	←	LP	0.876	0.394	0.176	4.992	***

Table 7. Model fit results.

CMIN	NPAR	CMIN	DF	P	CMIN/DF
Default model	60	727.280	291	0.000	2.499
Saturated model	351	0.000	0		
Independence model	26	3050.400	325	0.000	9.386
Baseline Comparisons	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0.907	0.941	0.952	0.8493	0.946
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000
RMSEA	RMSEA	LO 90	HI 90	PCLOSE	
Default model	0.052	0.047	0.068	0.000	
Independence model	0.144	0.139	0.149	0.000	
Parsimony Measures	PRATIO	PNFI	PCFI		
Default model	0.895	0.747	0.789		
Saturated model	0.000	0.000	0.000		
Independence model	0.895	0.747	0.789		

From the foregoing, it can be concluded the SEM had a very good fit, since all the Goodness-of-Fit tests were within the expected thresholds, in addition to the empirical model proposed by this work being valid.

Quantitative results: The findings substantiate that the strengthening of a loan model is motivated by an observed weak loan portfolio, demonstrated by high NPLs and bank failures. In the end strengthened loan models impact loan performance. The results reveal a need to align internal models with internationally developed models, resultantly, an improved, reliable model will be expected. On the one hand, it was observed some banks were not respecting model results. Moreover, the results reveal the rationale of loan model enhancement mainly focuses on model accuracy, model efficiency and model parameter soundness. Additionally, the study showed an internal model, developed using the logistic regression technique, is robust with a success rate of 87.80 percent. Therefore, the technique used in developing a loan model is more important than the number of variables used.

Qualitative results: According to the findings, the following are among the measures that impact loan model sustainability; guidance from regulator or central bank regulations; costs-effectiveness of the model; loan model is aligned to credit policy; and adjusting variables in line with the macro-economic environment; as well as reviewing loan model parameters based on previous loan model performance. Additionally, the main benefits of utilising a loan model are that it detects and distinguishes performing sectors from non-performing sectors and enables monitoring of borrowers. The study further argued that unabated challenges that confronted banks in operationalising loan models are largely due to an unstable macro-economic environment, uncertainty of political outlook and outdated data causing uninformed decisions. Nonetheless, findings reflect loan models are strengthened through the use of or incorporating guidance from central bank regulations and credit policy and by reviewing the successes of competitors' loan models. Thereafter, the banks should learn and adopt some useful variables missing from their loan models.

In our paper we therefore, argue that when the loan model is not aligned with international best practices, bank credit policy, regulator policies and prevailing macro-economic environment, the probability of that model providing inaccurate predictions is high. Furthermore, the bank must only apply quality data to achieve accurate results; this means data should be authenticated first, before being used. Failure to do so will result in the model providing a misleading score, with uninformed decisions consequently made by the bank, contributing to and resulting in NPLs.

7. Conclusions

The study deals with the effectiveness of Loan Portfolio Management Models also referred to as loan models, arguing that they are essential to ensure sustainable performance of Commercial Banks. Results proved that effective loan mod-

els yield quality assets, achieved through robust parameters, input and/or variables. It can be concluded that the features of a loan model are what make it effective, consequently, facilitating the selection of bankable projects by the banks. These findings confirm the results by (Ugoani 2015) [50].

It can further be concluded that although banks may develop or adopt best loan models, NPLs can be attributed to poor markets, hence loan models should have such a variable (market share) with a high weight. In addition, placing much reliance on international loan models contributes to NPLs, which exacerbate bank vulnerability. This is due to the non-applicability of some models, owing to information they require that may not be easily obtained from prospective or target markets (clients). In addition, applying an inappropriate loan model on a product may result in uninformed decisions, which cause NPLs. The study also argued an outdated loan model causes poor assets (NPLs), due to the variables used to assess borrowers being unable to cover all risk areas; this has a bearing on borrower performance. The study further shows that when a bank does not respect loan model outcomes, the probability of incurring NPLs is high.

It has been demonstrated that failure at the policy and practice level impacts the effectiveness of loan models, hence NPLs and bank closures. The study highlighted that some government policy, made through the RBZ, impacts macro-economic fundamentals. Consequently, high interest rates, inflation and exchange rates impact the economy, making borrowing expensive and resulting in clients defaulting (NPLs). Poverty is also a result of these poor policies, which impact loan performance. This work, therefore, reveals the need for constant review and alignment of loan models with local and global external environment changes, as this would assist with NPL mitigation.

This work has established loan model effectiveness is mainly affected by external factors (macro-economic and the political environment) more than the influence of individual factors. This makes it improper to rely on restrictive credit risk theories that do not account for externalities. Credit rationing theory is not precise on other variables that should be incorporated in an effective loan model. Similarly, portfolio theory is also not precise on the sector it should be applied to, therefore, the theoretical base does not accommodate all loan model variables. It can be argued that the failure of loan models is a result of a negative relationship between theories and loan models; this means theories miss some key factors that can be used to sustain and strengthen the loan models, given a constantly changing world.

In the study, it is also shown that only the bank perspectives were considered regarding the measurement of loan model effectiveness or credit risk. This suggests a high probability of bankable projects failing to access funding, due to clients not providing sufficient documentation for assessment. There is thus a high probability of attracting quality clients when they are aware of what the assessment comprises and obtain loans from banks only when they are aware of the criteria applied by banks for credit-granting decisions.

The study has validated that loan portfolio management in Zimbabwe is a

complex issue, evidenced by perceived politically driven policies, spearheaded by political players and or the government of the day. Some politically motivated changes in laws cannot, therefore, be ruled out, for example, a change of currency and or use of multi-currency is inconsistent with macro-economic policies. Consequently, these policies are seen as violating fundamental economic principles, which upsets the stimulation of the economy, as these policies have a direct bearing on inflation growth, surging of both interest and exchange rates, and this influences overall funding costs, making borrowing expensive and unsustainable.

Specifically, this work has shown a need for more intricate information on loan models, due to outdated data. Consequently, it is challenging to have loan models that can focus long-term in an unstable environment. What is critical at this stage, is for commercial banks to realise the need for other alternatives/technology-focused long-term. The study also highlighted that it would be erroneous to claim a bank may have a one-size-fits-all loan model. This is due to different clients having various requirements, both short- and long-term that call for a different approach or model. The study further proved the logistic regression technique is the best method to build a robust credit score model because it can determine the level of variable significance, making it possible to accurately predict future loan performance.

A further conclusion is that, overall, loan model effectiveness in Zimbabwe is fair, with a few institutions showing good loan models, as demonstrated by NPLs that vary from a single to two digits. The proposed ranking is based on validation methods such as the correct classification rate (percentage), meaning accurate prediction by a model Samreen, Zaidi and Sarwar (2013) [51], as well as analysis of percentage of bad loans (Desai, Crook and Overstreet Jr. 1996) [52]. The fact that NPLs peaked at 20 percent, contrary to the five percent of international best practice, demonstrates weaknesses in some loan models deployed by some Commercial Banks. The study, however, argued that the loan models have remained the main tool for selecting creditworthy clients in Zimbabwe, suggesting the NPLs and bank failures could have been much more rampant, had all commercial banks not utilised loan model results objectively.

8. Recommendations

This study has examined the tools used to assess the corporate loan application at the onset, yet, there are many facets of the NPLs that could still be examined to obtain a comprehensive picture of the causes of NPLs and the performance of loans by commercial banks.

i) Internal bank factors that contribute to NPLs should be examined. The bank is guided by internal policies that guide the final disbursement of funds to the borrower. It is imperative to appreciate the timelines and their feasibility, for example, when is the facility letter signed, the registration process of pledged security, and the liquidity position of the bank, among others. The study should, therefore, demonstrate how these processes may impact loan performance; in

the event of delays, given the client makes a loan application for funding in line with their budgets and or orders at hand.

ii) The relationship between loan model effectiveness and the number of years the bank has been in existence should also be evaluated. It is, additionally, important to evaluate this relationship for the following reasons: the background of the bank is important, whether locally or internationally founded may influence technology use or appreciation of modern models; factors that precipitate positive or negative correlation relationships will be observed; the study may argue on whether the number of years in its existence an influence on loan model performance has based on loan book growth.

iii) The security of the scoring system should also be studied. Scoring is computer-based; this means, that in the presence of cyber security challenges, including computer hijacking, it is important to ensure informed decisions are based on a secured system.

Conflicts of Interest

The authors declare no conflicts of interest.

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