



EXAMINING THE EFFECTIVENESS OF LOAN PORTFOLIO MANAGEMENT MODELS ON THE PERFORMANCE OF COMMERCIAL BANKS IN ZIMBABWE

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy: Business Administration

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Durban University of Technology

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MAY 2023

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Student Number: 21649306

A thesis presented in fulfilment of the requirements for the degree of

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In the

Faculty of Management Sciences

Of

Durban University of Technology

May 2023

DECLARATION

I declare that this thesis titled “**Examining the effectiveness of Loan Portfolio Management Models on the performance of Commercial Banks in Zimbabwe**” is my own work. All the sources used or quoted have been identified and acknowledged by means of complete references, and that this thesis has not been previously submitted by me for a degree at any other University.

Signed: _____

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I certify that the above statement is correct.

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ABSTRACT

The United States of America experienced phenomenal bank failures in the 1920s, which spilled over to other continents such as Africa and Asia. In Africa, Kenya, Nigeria, South Africa and Zimbabwe were some of the countries hardest hit by the bank failures. The main cause identified in all the instances, was an increased number of non-performing loans. Research in Zimbabwe has shown this problem became acute after the country obtained independence in 1980, persisting even though the Central Bank of Zimbabwe has tried to introduce several interventions on lending policy. At the centre of the lending systems of Commercial Banks are Loan Portfolio Management Models such as the Credit Score Model; the Z-Score Model and the Asset-Based Model, whose effectiveness have been examined in this study.

The overarching study aim is to establish how effective these loan models are in ensuring sustainable performance of Commercial Banks. To investigate these issues, a mixed method, sequential explanatory design was employed in investigating loan model effectiveness. The initial quantitative phase of data collection (survey) made use of a structured questionnaire with a 5-point Likert scale. Using a stratified sampling technique, data were gathered from 406 participants employed by 14 Commercial Banking Institutions in Zimbabwe. This captured data were analysed in SPSS version 24.0 and Analysis of Moment Structures (AMOS) v 24.0, to yield descriptive and inferential statistics. In the qualitative phase of the research approach, a structured interview was then employed to appreciate better and seek clarification of outcomes from the survey, by interviewing both ex-bankers and current 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 findings revealed the Credit Score model has been adopted by most banks, whilst the Z-score model was the least used model. Results also showed, in some instances, the features of a loan model impact effectiveness throughout the loan cycle. Furthermore, non-performing loans happen because of deficiencies of loan model parameters; characterised by outdated models, poor markets consequently insignificant cash flows generations, as well as inappropriate use of a loan model. This work has therefore, brought to light how loan models are perceived in the Zimbabwean banking sector. A negative relationship was found between credit risk theories and some loan models.

The implications of the findings to Commercial Banks include that loan models should always be reviewed to address credit risks brought by the prevailing business environment. Additionally, use of current data must be emphasised, as well as employing modern models, such as neural networks, which have proven effective in the developed world. The study's newly developed model, with an 87.87 percent accuracy rate, can assist banks to eliminate potential bad debts at onset and improve loan quality in the banking sector. The regulator is also expected to share important credit data, which impacts performance of loan models, as well as offering technical assistance to capacitate banks with lending skills. Moreover, the regulator should ensure pronounced policies are aligned to the macro-economic environment and long-term, in order that loan models are not paralysed. The government may motivate those banks with quality loans through tax breaks and ensuring GDP is strengthened, which will improve performance in all sectors, thus, mitigating NPLs. An area that should be further investigated is whether a relationship exists between a loan model's effectiveness and the number of years the bank has been in existence.

The key contribution to knowledge made by this study is, to the best knowledge of the author, the first study to simultaneously test the impact of the three most used models by Commercial Banks and determine that the Credit Score model has the capacity to meet a bank's requirements in identifying credit risks, particularly in a developing nation. Further to this, the study identified that parameter attributes of a loan model are key in measuring its effectiveness. The study successfully developed a loan model that can be used by a commercial bank through only applying relevant variables, which influence prediction of loan performance. In addition, structural equation modelling was validated as a most robust statistical technique for use in testing hypothesis skewed to loan models. Moreover, a key notable contribution is that credit risk theories only account for borrower characteristics, hence, there is a need to modify them by incorporating external factors, especially macro-economic factors.

ACKNOWLEDGEMENTS

I give glory to God for the blessing of good health which enabled me to endure the demands of this thesis.

I am most indebted to the Durban University of Technology and the Faculty of Management Sciences for providing the financial resources, without which this study would not have been undertaken, much less completed. To all the administrative personnel of the Faculty of Management Sciences of Durban University of Technology, particularly Jeslyn: You are a star. Thank you for your invaluable support and for tolerating my many requests which I invariably made at the most inconvenient times.

In Dr Potwana, I had an able and patient supervisor. I have no doubt that I tested her patience to the limits with my endless need for guidance. Dr Potwana went beyond the call of a supervisor and provided encouragement when my own faith in this undertaking was waning. I will forever cherish her stimulating intellect and knowledge of the subject matter.

My research assistants did a marvellous job and I deeply appreciate their tireless efforts towards the success of this study. Gary Analytics, thank you for always knowing what to do with data. My language editor, Dr Helen Richter, thank you for all the corrections and your effort in editing my work. Last, I cannot thank my family enough. They bore the brunt of my perpetual absence from home during the course of my study. To my parents, thank you so much. Your love for education inspired me to undertake this study.

DEDICATION

TO THE VUSAs

KIKI; ZOE; TAD and SHEILA

FOR YOUR FORBEARANCE!!

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LIST OF ACRONYMS

AIC	Akaike Information Criteria
AUC	Area Under Curve
BCCZ	Bank of Credit and Commerce of Zimbabwe
BYO	Bulawayo Province
CBSEM	Covariance based Structural Equation Model
CFA	Confirmatory Factory Analysis
DUT	Durban University of Technology
EBA	Empirically Based Attributes
EBA	Evidenced Based Attributes
ERM	Enterprises Risk Management
EFA	Exploratory Factor Analysis
FINHOLD	Zimbabwe Financial Holdings
GBP	Great Britain Pounds
GDP	Gross Domestic Product
HRE	Harare Province
IFC	International Finance Corporation
IMF	International Monetary Fund
KMO	Kaiser Meyer Olkin
LPM	Loan Portfolio Management
LPMA	Loan Portfolio Management Model Attributes
LPMM	Loan Portfolio Management Model
LR	Logistic Regression
MCP	Manicaland Province
MCP	Mashonaland Central Province
MDP	Midlands Province
MCP	Mashonaland East Province
MP	Masvingo Province
MSP	Matebeleland South Province
MTN	Matebeleland North Province
MWP	Mashonaland West Province
NPL	Non-Performing Loans

PCA	Principal Component Analysis
PESTEL	Political, Economic, Social, Technology, Environment and Legal
RBI	Reserve Bank of India
RBZ	Reserve Bank of Zimbabwe
ROC	Receiver Operating Characteristics
SA	South Africa
SRO	Senior Risk Officer
SMEs	Small and Medium Enterprises
SME	Structural Equation Model
USA	United States of America
USD	United States Dollars
VBSEM	Variance Based Structural Equation Model
VIF	Variance Inflation Factors
ZAMCO	Zimbabwe Asset Management Company
ZAR	South African Rand
ZSE	Zimbabwe Stock Exchange

CHAPTER ONE

ORIENTATION AND OVERVIEW OF THE STUDY

1.1 Introduction

Subsequent to adopting a multi-currency system in 2009 and without the Zimbabwe dollar undergoing a conversion process, the Zimbabwean financial sector that has developed in recent years continues to under-perform. The confidence loss in the financial sector, adverse effects of hyperinflation and subsequent financial reforms/reform reversals, resulted in studies that thoroughly examined various aspects of Zimbabwe's banking sector, highlighting an array of factors contributing to financial reforms and/or their reversal. Although financial reforms are generally a precursor to growth, they have also been shown to result in negative welfare effects, including macroeconomic instability. In the process, poor reform design and implementation have become evident, further highlighting the lack of donor support, along with insufficient political resolve to persist with reforms, which have resulted in the reversal of policies.

In light of this, the *“effectiveness of loan portfolio management models on the performance of commercial banks in Zimbabwe”* was examined (2009-2018) in this study, indicating that while an economic crisis can be induced by poorly managed and ill-timed financial reforms, this restructuring and transformation remain critical to the country's strategy for economic growth and transformation. The inferences drawn from the development of this study show a need for more in-depth financial sector reforms in Zimbabwe, so that a broad spectrum of products is developed and implemented to meet the demands of the investing public, with procedures and processes in place to monitor performance measures, allowing the financial sector to not just stabilise but also grow.

The study focusses on the effectiveness of the loan models in loan portfolio management (LPM) in Zimbabwe's Commercial Banks. This chapter outlines challenges of banking business and loan quality in Zimbabwe. The problem is demonstrated precisely and gaps in current knowledge are identified, with a description of the study focus, while it also reiterates the study objectives as well as

the proposed hypotheses. The relevance and rationale of this work are explored, while contributions derived from the study are also brought forward.

The instability in the current global economic environment has prompted banks to effect drastic measures in credit portfolio management, with this adoption suggesting inadequacy of existing tools, such as loan models (Mileris 2012; Anagnostopoulos *et al.* 2018). Furthermore, these enormous changes impact bank profit from loans granted, exhibiting poor-quality assets, hence, credit risk assessment has become a major area for reform at many financial institutions (Beck *et al.* 2008). Zimbabwean financial assets are dominated by loans and the high incidence of Non-Performing Loans (NPLs) poses significant risks to the health of Zimbabwean financial institutions (Banks Annual Reports 2014; RBZ 2018).

The importance of effective loan models and credit risk management was underscored by Levine (2003) and Bolton *et al.* (2019), who argued that banks stimulate economic development when the financial system in place is sound. This study, therefore, validated some well-established loan models, developed 50 years ago, considered applicable in Zimbabwe and globally. This has been achieved through primary data obtained from bank practitioners of operating banks, as well as from ex-bankers who possess practical experience. The data were obtained through a questionnaire and personal interviews.

The motivation for the study is the need to test the effectiveness of loan models in a developing nation such as Zimbabwe. This work argues that, amid highlighted threats and challenges in the Zimbabwean banking sector, banks need to remain afloat by retaining high quality assets, through improved LPM, informed by effective loan models. The knowledge gained is relevant to financial institutions and regulators alike in Zimbabwe.

1.2 An overview of Loan Models and Portfolio Management

The mainstay of bank revenue is generated by performing loans, making it necessary for the Commercial Bank to attract quality borrowers because bad loans cause loss of bank capital and bank failures (Sreedhar *et al.* 2011; Shaffer 2012; Li 2013; Khaled & Wahab 2019). On the one hand, quality clients may only be achieved by use of

loan models, as argued by Abdou and Pointon (2011). On the other hand, the risk posed by NPLs has resulted in a global financial crisis (Saeed & Zahid 2016). In the interim, Lagat, Mugo and Otuya (2013) emphasise the need for banks to manage their loan portfolios; to be successful a bank needs to have quality assets, evaluated through effective loan models and LPM, which is the subject of this study.

Importantly, globalisation, spurred by an unstable economic environment, is prompting banks to strengthen their LPM (Mileris 2012; Anagnostopoulos *et al.* 2018). Failure by banks to mitigate credit losses attributed to the financial crisis of 2007-2008, exhibits the need to use sound tools in evaluating and monitoring loan books, such as loan models (Antão & Lacerda 2011). It is, therefore, essential that applicable and effective loan models are developed and utilised to mitigate credit risks currently faced by banks (Lai & Kuo 2010; Tursoy, 2018). Grice & Dugan (2003) argued that various loan models have been developed by various scholars and or theorists, however, the major drawback is that they were developed by means of different methodologies and have been in existence for too long, hence, the argument is that they suit an unpredictable business environment. Furthermore, lending institutions such as Commercial Banks are cognisant of various risks, particularly credit risks, which motivate them to fully comprehend and quantify such risks, thus enhancing their LPM (Al Baz 2017; Tursoy 2018).

Kuritzkes (2002) argued that in a large banking institution credit risk is the most outstanding risk and can only be quantified by a tested loan model. Additionally, for banks such as a Commercial Bank to achieve and sustain a clean loan book, they also need to employ experts or skilled people with capacity to compute and determine credit risk level from the outset, hence, only lending to creditworthy clients (Collins *et al.* 2009). Banks are not only financial intermediaries but are further considered as credit risk intermediaries because they often monitor and measure credit risk using loan models and take precautionary or migratory measures that will not threaten the soundness of a bank, principally solvency and loan portfolio (Lai & Kuo 2010; Rehman *et al.* 2019).

Scientific methods, such as loan models in evaluating loans, are considered more appropriate tools to employ, as opposed to traditional practices that rely on history or

trailing of loan performance; for example, level of delinquency or risk grade of a client, which may delay appropriate action by banks because there is no lead of credit risk using these methods (León 2018). In addition, traditional methods employed by banks to evaluate loans, such as judgemental, are now being discarded by most banks as they do not give a score that indicates the risk level of a borrowing client (Wang 2013).

Credit risk management is prominent in a Commercial Bank, focuses on retaining quality assets and has been enhanced through the use of loan models from the outset throughout the loan cycle (Fraser & Simkins 2010; Wang 2013; Madeira 2018). Similarly, Abiodun and Entebang (2015) and Coetzee and Buys (2017) argued that due to the different risk dynamics carried by various clients from all sectors, reliance is now being placed on statistical models to manage credit risk more accurately. It has, furthermore, been noted that most banks have an extra mile when they develop an internal statistical model also used in rating borrowing clients to determine bankability of their projects (Berger 2004; Gakure *et al.* 2012; Wang 2013; Li & Zou 2014). In addition, Horstedt and Linjamaa (2015) argued and supported the use of quantitative models that exhibit reliability.

Nonetheless, loan portfolio is made up of clients who have benefited from loan products of a bank such as a Commercial bank and these loans can be categorised as personal loans as well as commercial loans, respectively for individuals and for companies (Murugu 2010; Kurui & Kalio 2014). Furthermore, for a portfolio to be considered as successful, it means borrowers will be performing or paying their loan repayments timeously. This also suggests that for a bank to achieve quality assets, strict credit control mechanisms should be in place, in addition to the use of effective tools such as loan models to distinguish potential bad debts from creditworthy clients.

Onuko, Muganda and Musiega (2015) argued that a loan portfolio is considered of good quality only when there are few NPLs and a sound loan portfolio is an edge to any institution as it improves profitability, the liquidity position of the bank and the general financial sector of the country. There is thus a need for a thorough evaluation exercise on all new loan applications, using tools or techniques that are reliable and can guide the bank in making informed decisions. Additionally, the bank should not

only concentrate on maintaining credit risk of one client but for the entire portfolio, as any loan that may be occasioned will impact the entire institution.

LPM entails that a bank is secure; in other words, all loans are performing according to the contract. This is achieved only when a bank manages to identify and control all risks inherited at inception, as they were considered insignificant (Chodechai 2004; Kanapickiene & Spicas 2019). Gonzalez-Paramo (2011) and Agrawal and Maheswari (2019) also asserted that for a bank to fully appreciate credit risk of its portfolio, there is a need to utilise additional tools, suggesting the use of loan models at evaluation stage, as well as when monitoring loan performance or quarterly reviews that will indicate whether a client still carries a low credit risk.

1.3 The Knowledge Gap

Numerous studies have evaluated client creditworthiness from different sectors, using various methods, including loan models (Berger, Frame & Miller 2005; Anderson 2007; Chung & Lin 2009; Paleologo, Elisseeff & Antonini 2010; Gowri & Sekar 2014; Hsu 2017). Various results obtained do not conclusively show that loan models offer full assurance of quality loans through its entire term and/or bank portfolio. For example, Hsu (2017) found models such as Z-Score, were more effective in certain industries, for instance, aviation. However, no details were further made available on how this model impacts bank loan performance. Nevertheless, NPLs still exist, despite the use of loan models (RBZ 2014). There is thus a gap in knowledge, with insufficient literature addressing bank failures using loan model effectiveness in Zimbabwe.

Loan models such as Internal Credit Score play a critical role in lending decisions. Model use would, therefore, improve the capacity of bankers to distinguish potential clients from defaulters (Rezac & Rezac 2011; Bhardwaj & Sengupta 2011, 2015). However, the global scale of NPLs contributing to bank failures, is attributed to ineffectiveness of some loan models (Saba, Kouser & Azeem 2012; Li 2013). This makes it important that loan models are given prominence, allowing banks to deal with lending activity impact. The study thus strengthens the existing knowledge gap on use and types of lending tools (loan models) that may lead to and facilitate enhancement of credit management in Zimbabwe's Commercial Banks. Moreover,

study results have the potential to influence bank management in putting loan models in place that protect financial institutions, in particular Commercial Banks.

Bank failures or closures result in negative sentiments from various stakeholders and the Reserve Bank of Zimbabwe (RBZ) consequently warned that public confidence in the banking sector needs to be restored (RBZ 2011). Doing so means the practicality of loan models need to be reviewed. Although loan models have become a focus of scholarly enquiry of late, there is a knowledge gap on the practicality of loan models developed more than 50 years ago in a stable environment, for example the Z-Score model; contrary to the Zimbabwean business environment, which is unstable and very unpredictable both in macro-economic fundamentals as well as politically. Furthermore, applicability of the loan models to all sectors of the economy, given that some loan models are tailor-made for specific sectors, clientele or according to a bank's risk appetite, with varying cut-off scores and variables, motivate the need for a study.

In Zimbabwe, Nyangara (2013) examined the Asset-Based model and the findings show that it is an effective tool only in the presence of suitable security. Dondo (2019) found that the Z-Score can successfully evaluate construction industry companies. Nonetheless, most of the studies were limited to specific topics of interest. For example, Chikoko, Matambanadzo and Vhisimai (2012) bemoaned Zimbabwe not having its own currency; Dzomira (2014) focused on bank crises and did not isolate loan model effectiveness; and Kithinji and Waweru (2007) researched only Kenyan Commercial Banks, with McMillan's (2014) study not viewing global loan models, which may impact commercial bank loans. Therefore, there is a need to close the gap on loan model/s suitable for a developing nation such as Zimbabwe.

1.4 Focus of the study

This study explores LPM model effectiveness on commercial bank loan performance in Zimbabwe, for the period of 2010 to 2018. The study focused on loan models used to evaluate commercial loans because of large amounts borrowed that expose banks to credit risk (RBZ 2018). This study has, therefore, firstly focused on the financial architecture of the country, as well as its economy, dating back to pre-independence (1980), and how these affect LPM (Chapter 2). Zimbabwe continues to lose players

in the financial sector as bank failures and closures remain unabated due to NPLs which remain high and peaked to an all-high level of 20 percent of total loan books, as opposed to international accepted levels of five percent of total loan books, as per Basel ii (RBZ 2009, 2014). The banking sector did record some exponential growth between 1992 and 2004, prior to serious bank challenges and threats experienced, as revealed by Muranda (2006) in the growth patterns (Table 1.1) below;

Table 1.1: Financial sector growth patterns in Zimbabwe

Type of Institution	1992	2002	2003	2004	Growth %
Commercial Bank	5	15	17	16	220
Merchant Bank	4	6	6	6	50
Finance houses	4	7	7	5	25
Discount houses	3	7	8	9	200
Building Societies	3	5	5	5	67
Sector-wide growth	19	40	43	41	115

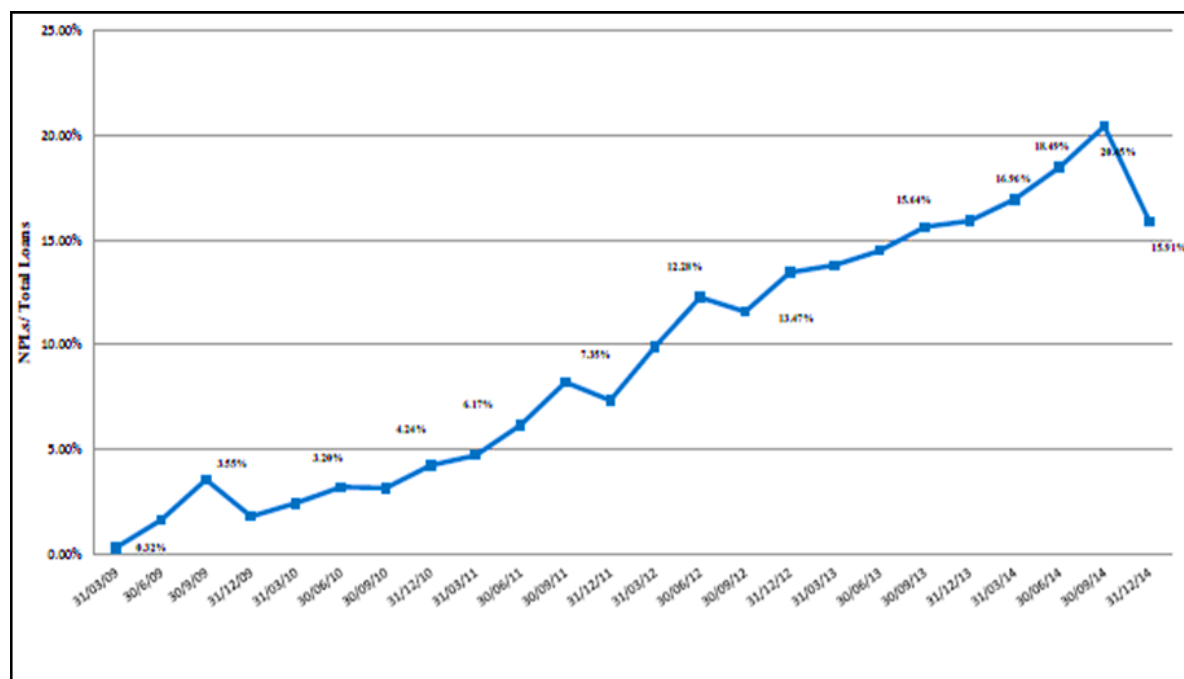
Source; Muranda (2006)

The growth of note recorded by banks were followed by several failures, attributed to various reasons, among them poor credit risk management, which caused NPLs, poor corporate governance, and inadequate capitalisation (Mumvuma 2002; Muranda 2006). Zimbabwe has lost 20 banking institutions since 1980 among them are; Allied Bank, Afrasia Bank, Barbican Bank Limited, Century Discount House, CFX Bank Limited, ENG Capital, Intermarket Banking Corporation Limited, Intermarket Building Society, Interfin Bank, National Discount House Limited, Rapid Discount House, Renaissance Merchant Bank rebranded to First Capital, Royal Bank Zimbabwe Limited, Time Bank of Zimbabwe Limited, Trust Bank Corporation Limited, United Merchant Bank, Unibank (Dzomira 2014 ; Dhliwayo 2015), exhibiting a dearth of information, hence the need to focus on this sector and the tools used to assess loans, such as loan models.

During the period under review, NPLs in Zimbabwe started within the acceptable range as per Basel ii recommendations of five percent (Basel Committee

on Banking Supervision 2004), however, this was breached in 2011 when it stood at six percent, thereafter, it started to increase.

Table 1.2: NPLs in Zimbabwe



Source: RBZ (2015)

The NPLs steadily increased from 0.32 percent (2009) to 16 percent (2014). This upward trajectory was attributed to general poor-quality assets. Nevertheless, two banks were closed in the last quarter of 2014 and this impacted positively on the NPL ratio, which stood at 20 percent in the third quarter of 2014. The high NPL, therefore, requires an examination of the effectiveness of LPM models as a lending tool at inception. However, inflation was reasonably low during the period under review, suggesting the economy was stable, and loans were also expected to be performing (ZIMSTAT 2017).

Table 1.3: Inflation Rates

Year	2010	2011	2012	2013	2014	2015	2016
Inflation rate	3.1	3.	3.7	1.6	(0.2)	(2.4)	(1.6)

Source: ZIMSTAT (2017)

Despite stable Inflation rates, which suggested a performing economy, the banking sector still experienced NPLs (RBZ 2016). This therefore highlights the need to focus on this sector. Furthermore, due to the transformation of world markets, the study examined lending tools, which are loan models (Chapter 3), while also tracking literature of both developed and developing countries on the background of various loan models, their evolvement, success stories globally, as well as concerns, and argumentation. Additionally, the manner in which these loan models' effectiveness can be measured by Commercial Banks for their continuous use was investigated. Although there are various loan models, the study shall link three models, namely Internal Credit Score, which is interchangeably referred to as the Credit Score model, Z-Score (1968) and Asset-Based models.

Zimbabwe Commercial Banks hold loan tenure for up to five years, excluding mortgage (Commercial Banks annual reports 2014). In this regard, Durand (1941) stated a Credit Score model can forecast bankruptcy five years ahead, making it applicable in a Zimbabwe commercial bank. Berger and Frame (2011) observed that in developing countries, the models are widely in use, particularly in financing SMEs. Thirdly, Internal Credit Score, Z-score and Asset-Based models are well-established (50 years old) and tested in both developed and developing countries for extended timeframes and are reviewed or improved, solidifying them in the process (Rezac & Rezac 2011). The importance of reviewing their effectiveness in the Zimbabwe commercial banking sector, which has suffered poor loan quality, despite a stable currency and environment during the period under review is thus imperative (RBZ 2018).

Similarly, studies (Nyangara 2013; Mpofu & Mukosera 2014; Hlongwane *et al.* 2014; Mutava 2015; Dondo 2019) have shown that loan models such as Credit Score, Z-Score and Asset-based models, are used in Zimbabwe to predict future performance of borrowers and or predicting future bankruptcy of companies, hence these models are considered suitable for Zimbabwe and other developing countries. The studies did not, however, demonstrate how they may influence loan performance or LPM in the entire commercial banking sector, which influences the country's banking system. This study will empirically test evidence on these models and or any other models deemed suitable for Zimbabwe, as shown favourably by practitioners. This study

argues that practitioners should find ways to apply old traditional loan models, as these should be effective in evaluating bank loans, despite the state of the economy.

1.4.1 Why Commercial Banks in Zimbabwe

Many lessons can be drawn from Zimbabwe by other Sub-Saharan African (SSA) countries and Africa in general because of its peculiarity, as exhibited by remarkable challenges both fiscal and monetary, including liquidity, hyperinflation, interest rate volatility, and de-industrialisation (Ndakaripa 2020; Mpofu 2015; Sikwila 2013). Moreover, Zimbabwe is among those developing nations in Africa whose financial sector is dominated by Commercial Banks, therefore, they dictate and control lending. As a consequence, poor loan underwriting may impact the entire financial system, hence, the need to upscale knowledge on lending tools (Bamper *et al.* 2014). Furthermore, Zimbabwe, as with other SSA countries, grant loans to all different company sizes, including SMEs, making it important to test the applicability of the loan models under study (Bamper *et al.* 2014; Nyamwanza 2014; Ross, Ligang & Cai 2018).

Not only is the Zimbabwean economy affected by hyperinflation, other factors include political difficulties, as a result society and all sectors of the economy, including bank performance, are negatively affected (Hanke & Kwok 2009; Makoni 2014; Pasara & Garidzirai 2020). The country's industry was funded by various financial intermediaries just after independence in 1980 and these comprise; finance houses, merchant and commercial banks, as well as building societies until 1991, after which the economy disintegrated, following the introduction of Economic Structural Adjustment Programmes (Mutenheri & Green 2002; Phimister 2000). Additionally, both political and economic instability, as well as international isolation confronted the banks, with bank failures recorded as a result (Mutenheri & Green 2002; Phimister 2000; Calomiris and Haber 2014). However, funding sources have since narrowed to Commercial banks, making it necessary to study loan models in this unique country. African Development Bank (AfDB) explained that Zimbabwe is among a few countries that have “dollarized” their economy due to social and economic instability, though the economy started to rebound between 2009 and 2012, after which it subsided again (AfDB 2014). The dynamics and never stable economy result in developing countries learning the practicality of loan models.

This study selected Commercial Banks because they dominate the financial sector and are major funders of commercial activities, hence, they carry major risks inherited in loan portfolios (RBZ 2018). Additionally, Commercial Banks are considered as national enablers and facilitate development in an economy requiring the use of reliable tools when evaluating borrowers. Benefits to the Commercial Banks from this study are varied, such as: use of a reliable loan model or models, doing away with any subjectivity when lending and better objectivity at the outset of any project evaluation. Moreover, timeous and consistent evaluation and monitoring of commercial loans will be possible using the most appropriate model, while the commercial banks will most likely retain quality loans due to a reliable loan model, in addition to preserving capital of Commercial Banks due to reduced NPLs.

1.4.2 Relevance of Study to Zimbabwe

Laiboni (2012) argued asymmetric information negatively impacts the banking sector before and after a transaction has been closed (moral hazard). This makes it imperative to review loan model performance, as some borrowers do not disclose all their information. According to Labonte (2013), the interconnection between “too big to fail and moral hazard theories” has been one of the ways of explaining bank failures. The ‘too big to fail’ (TBTF) theory views the bank as large and with mature systems that use precautionary measures such as loan models in their loan evaluation process.

Scientific research obtained during this study indicate the necessity to guide Commercial Banks, as well as other lenders such as building societies and microfinance operations, to achieve sustainable loan performance. The knowledge generated by this study is expected to assist stakeholders to appreciate the effectiveness of loan models, providing some insights into the importance of loan models. This analysis becomes more relevant in the Zimbabwean context because there is a serious lack of evidence of notable studies that link the three models and their impact on the quality of Commercial Bank loans. Therefore, the insight provided into the use of loan evaluation tools required study, including their banking sector performance. The study anticipates its outcome(s) will influence executives in the Commercial Banks in Zimbabwe and the Finance Ministry on the need to review the country’s various loan models and how these models may influence loan

performance in the future to proactively determine potential NPLs. Moreover, study results have the potential to influence bank management in implementing loan models that protect financial institutions, in particular Commercial Banks. This study adds to the loan models effectiveness debate on loan performance sustainability, as a solution to the mitigation of bank failures. Consequently, more funding will be channelled into the economy by more banks, resulting in better Gross Domestic Product (GDP) for Zimbabwe.

1.5 Preliminary Literature Review

In this section, a brief literature review is presented as it guides this study, the models under study are introduced, namely Internal Credit Score, Z-score and Asset-Based, along with definitions, prior to being unpacked in the literature review chapter. While bank loan performance is an overview of bank loans and how loans are qualified as either performing or NPLs; including causes of such a category, loan model effectiveness reflects the way banks measure the efficiency of the loan model under use.

- **Credit Score Model**

According to Berger and Frame (2007) and Liberati, Camillo and Saporta (2017), 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 (Schweser 2013). The scores of the model show client capacity to service a monthly loan instalment or not, based on set benchmarks. Any system used to evaluate risk associated with a borrower produces credit scores assigned to borrowing clients that exhibit the risk level of the prospective borrower to the lender (Gestel & Baesens 2009). 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 any item or aspect that identifies risk threatening repayment capacity of a borrower can be weighed.

- **Z-Score Model**

This model is defined by Altman (1968) as a quantitative measure used to forecast bankruptcy or failure of a financial entity. The Z-score model may also, according to Al-Manaseer and Al-Oshaibat (2018), 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 and below, the risk is high (Lando 2004; Altman 2018). The classification of clients is on the back of cut-off value and all the variables should be positive to attain a good Z-score (Meeampol, Srinammuang & Rodpetch 2016).

This work tested the Z-Score of failed banks using 2011 financial statements before they collapsed. The results show all banks which had negative Z-scores closed, however, there was one exceptional bank which had a positive Z-Score but also collapsed. (See Annex 6a). Notwithstanding using the Z-Score model to predict future loan performance of their clients, they failed to utilise the same model to determine their own future performance.

- **Asset-Based Model**

As explained by Marks *et al.* (2009) and Wang and Li (2021) Asset-Based Lending is a revolving loan, hence 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, are referred to as Asset-Based Lending (Sprenger 2013). 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.

Ollows and Moro (2015) 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 in the event of instalments not being timeously paid.

1.5.1 Effectiveness of Loan Models

With regard to Credit score, Schweser (2013) argues that the following formula can be used to measure prediction performance of the Credit Score model (internal) and the Asset-Based model; in other words, utilise computing to evaluate the credit rule by means of how many defaults were correctly predicted and number of firms predicted to default that did not. The formulae are, respectively:

1. $Y = \frac{\text{Number of defaults correctly predicted}}{\text{Number of defaults}}$
2. $X = \frac{\text{Number of firms predicted to default and did not}}{\text{Number of firms that did not default}}$

Application of 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.

Page and Meyer (2006) 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 more elevated the ordinal score, the more the ability of the model improves in distinguishing those most likely from those least likely to go bankrupt. The following formula was proposed by Page and Meyer (2006) to establish effectiveness of loan model such as Z-Score:

$$X = \sum_{i=1} PBK_{i,x}$$

Where:

PBK_{i,x} = number of companies in decile *i* that went bankrupt within x years
= 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 actual 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 future failure of a client is not identified or predicted by the model, whilst a Type ii error denotes classification of a creditworthy client as a likely bad debt and the application is declined. Therefore, to measure the performance of a loan model, there should be some predefined characteristics.

1.5.2 Bank Loan Performance

A bank loan refers to money granted for business purposes and includes financial terms and obligations (Arnold 2014). These terms comprise a tenure in which amortisation shows capital, as well as interest, which should be paid at a given date,

with varied tenure that could stretch anywhere between one to seven years and in some circumstances, extend to 20 years.

There are various factors that influence Commercial Banks' decisions to extend loans to different sectors. One of these is liquidity ratios, with Pilbeam (2005) drawing attention to the total amount of liquidity within a bank necessitated by loan requests from prospective clients. A high number of requests for loans decreases liquidity availability. When loan requests are low, banks tend to retain short-term assets, referred to as liquid assets. However, when loan requests are high, banks reduce the levels of liquid assets, as long-tenure loans yield better margins. In this regard, the capacity for a bank to grant loans is enhanced by sufficient liquidity.

Commercial Banks are also guided by interest rates, which Castro and Santos (2010) explained as the cost factors for bank loans, used as determinants to grant loans. This suggests the appetite for borrowing and lending is propelled by client affordability or capacity to pay back the loan on the specified due date. The higher the interest rate, the more expensive it becomes to access funding. There are two categories of loans, namely performing and non-performing.

Performing Loan: A loan is considered to be performing when it is repaid along with the interest payments, without any delay (Obamuyi 2007). Furthermore, any loan in arrears for less than 90 days is considered as performing (Grieser & Wulfken 2009; Rose & Hudgins 2010; Mulyungi & Mulyungi 2020). Essentially, the bank can book income from the interest being generated by this loan. There are mainly three components of a performing loan, one of which is an Agreement. The said Agreement is a contract signed by the borrower and the bank (Rose & Hudgins 2010). The contract explicitly states the loan terms, principal amount, applicable interest rate and repayment due dates. Furthermore, there are also covenants in which financial documents are expected from borrowers in the form of management accounts, debtors and creditors, aged analysis and stock returns, used for monitoring client performance by the Commercial Bank (Brown & Moles 2014).

Security: Security is an asset used as a fall-back position by a bank and type and value should be precise (Inderst & Mueller 2007). The loan agreement on the required security is precise (Rose & Hudgins 2010).

Interest and Principal: Principal is an amount of loan that remains unpaid at any given time (Rose & Hudgins 2010), which means it is effectively the total amount the bank disburses to the client. 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 to be generated from loans extended to clients is referred to as interest. An example of how interest is calculated is shown:

$$I=A \times i/c \times N$$

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.

Non-Performing Loans: The instant whereby a loan ends earnings to a lending institution, is classified as an NPL (Popli & Puri 2014; Mulyungi & Mulyungi 2020). 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 during a 90-day period. A good example is of a farmer whose two cropping season instalments are not paid because of recurring droughts.

The following are examples of financial factors that cause NPLs.

Interest Rates: The RBZ (2015) observed that NPLs 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.

Gross Domestic Product (GDP): Brezina (2012) describes GDP as 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 market value when the economy is performing. However, when the economy is depressed, unemployment increases, consumers' disposable income falls and corporate revenues, which are sources of loan repayments, also decrease.

Inflation: This is the frequency at which the prices of goods or services change (Donovan 2015; Jongrim Ha, Stocker, & Yilmazkuday 2019). 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.

Exchange rate: The price of a different currency in a foreign exchange market is termed an exchange rate (Moosa & Bhatt 2009; Kalu & Mike 2020). Fluctuations in the exchange rate, where the trader imports most inputs, makes products more expensive and results in low sales that reduce the capacity to service debts, with resultant NPLs.

1.6 Definitions of Terms

Terms used widely in this study are briefly described:

Table 1.4: Definitions of terms

	TERM	DESCRIPTION
1.	Bank	Any financial institution licensed by a regulator or central bank to accept deposits and grant loans is referred to as a bank, for example commercial banks (Rose & Hudgins 2010)
2.	Bankruptcy	Sajjan (2016) explained bankruptcy as a situation in which the total liabilities of a firm exceed the total assets. The company is thus incapacitated, making it impossible to service debt
3.	Applicant	An applicant is either a corporate or an individual with an account held at a bank, and anyone who has access to funding goods or services without paying upfront for the

		cost and who, instead, settles all dues as per agreed future dates (Gomez 2012; Popli & Puri 2014)
4.	Credit Score	A Credit Score is a quantitative expression, constructed on the individual or company characteristics or credit files to demonstrate creditworthiness of the applicant (Thomas, Crook & Edelman 2017; Samreen & Zaidi 2012). It evaluates the probability of clients servicing debt in the near future and clearly shows client capacity to service the debt
5.	Principal	Total loan amount disbursed to a borrower as well as any outstanding money during tenor of a facility is referred to as principal (Rose & Hudgins 2010)
6.	Interest	The cost applied when borrowing is referred to as interest and most interest rates are regulated by the regulator (Castro & Santos 2010)
7.	Default	Default refers to a situation where there is a risk of borrowers failing to service their debt monthly (Bessis 2010)
8.	Efficiency	Efficiency is the ability to not waste materials, time or energy when doing or producing something (Wilson <i>et al.</i> 2018)
9.	Effectiveness	Effectiveness refers to the power to generate the preferred result (Wilson <i>et al.</i> 2018)
10.	MDA	Krishnaswamy, Sivakumar and Mathirajan (2009) state that Multi Discriminant Analysis (MDA) is a statistical technique that is multivariate dimensional and diminutive, mainly used to predict and support the classification of borrowing clients. It applies to more than one variable and shows the relationship between multiplicities of variables
11.	Performing Loan	A performing loan is wherein all terms are respected; this means capital and interest are timeously paid and or arrears are not beyond 90 days (Grieser & Wulfken 2009)
12.	Non-performing Loan (NPL)	A NPL is wherein all terms are not respected, thus, the client has failed to service monthly instalments and arrears are beyond 90 days (Grieser & Wulfken 2009).
13.	Security	Any valuable immovable and moveable assets, for example, a house and factory equipment accepted by a bank as a fall-back position in the event of default, are referred to as security (Gomez 2012; Popli & Puri 2014)

14.	GDP	The GDP of any country measures values of finished goods and services within a country's borders that are computed as; personal consumption plus private investment plus government spending and exports less imports (Brezina 2012)
15.	Inflation	A country can measure broad movements of local prices and or cost of living through Inflation. It reveals the rate of price increases at any given time or period (Donovan 2015)
16.	Exchange rate	Exchange rate may be referred to as the value of a country currency with the objective of converting to another country currency, for example, exchange of Zimbabwe dollar against the South African Rand (Moosa & Bhatt 2009)

1.7 Problem Statement

According to the RBZ (2019), between the years 2010 and 2018, several banks in Zimbabwe were closed. Some of these banks include CFX Bank and Premier Bank that failed in 2010, prior to being taken over by Interfin and Ecobank, respectively. Furthermore, other banks affected included Genesis Investment bank that failed in 2011; Royal bank that failed in 2012, Trust bank that failed in 2013, Capital bank and Interfin bank that failed in 2014, and both Afrasia and ZABG that failed in 2015. In addition, Tetrad bank and Metbank were placed in the troubled banks category due to perennial solvency weaknesses attributed to NPLs. However, many reasons have been adduced for such failures. These include poor quality assets, hence high NPLs that deplete capital; poor corporate governance; inadequate skills of lending personnel; and lack of effective credit risk measures such as loan models; as well as inadequate capital (Dzomira 2014; Kohli 2013; Chinjova & Zinhumwe 2019).

The RBZ (2014) attributes bank challenges and closures to developments post the dollarization era, during which credit quality has been steadily falling. The major cause of this dramatic decline was mainly attributed to NPLs (RBZ 2014). The average loan performance in Zimbabwean Commercial Banks does not correspond with the international acceptable standard of five percent, as prescribed by Basel ii (Basel Committee on Banking Supervision 2004) in comparison with the highest average peak which is at 20 percent (RBZ 2015).

These bank failures have also led to other negative consequences, such as loss of jobs in the sector. According to official statistics by the Zimbabwe Allied Workers Union (2014) representing bank employees, approximately 1 000 bank workers' employment contracts were terminated between 2009 and 2014 due to the closure of nine banking institutions, of which six were Commercial Banks. The bank workers' union reacted by sending a petition to the National Assembly, recommending a national disaster of bank failures be declared and calling for a review of licencing and regulation of banks (The Zimbabwe Independent 2015).

Following a public outcry, as well as Government concerns, the then Bankers Association of Zimbabwe President, Mr George Guvamatanga, was summoned to the Zimbabwe Parliament. He was asked several questions regarding the loan quality in Zimbabwe before the Finance and Economic Development Portfolio Committee, admitting to the existence of high NPLs. Guvamatanga also shared that while banks had varying levels of NPLs, the average had breached the international standard of five percent, making it imperative to produce a lasting solution to ensure banks adhere to international best practices (The Zimbabwe Independent 2015).

Commercial Banks in Zimbabwe still claim the use of loan models, notwithstanding that bank failures are attributed to various reasons, including NPLs. Allen, De Long and Saunders (2004) contend these loan models used by the institutions are critical at the outset of loan evaluation, utilised to select potential good clients, as evidenced by good scores obtained during credit rating. Loan models such as Internal Credit Score, Z-score and Asset-Based models are effective tools used by Commercial Banks in selecting and focusing future performance of a borrower and potential bankruptcy, evidencing the importance of assisting banks in identifying only bankable projects (Durand 1941; Altman 1968, 2018; Orgler 1970; Thomas 2000).

Alternatively, it is proffered that the Z-Score model cannot detect manipulated data on financial statements (Eidelman 1995; Begley, Ming & Watts 1996; Bemmann 2005; Altman 2018), due to the model accuracy rate diminishing for longer terms, consequently pointing out that the prediction is not always constant as claimed by bankers. Conversely, Kunt and Detragiach (2010) defended the Z-score model by stating that it has not been responsible for company failures and NPLs but instead

attribute these to the lack of regulator or management soundness. Rao *et al.* (2013) assert that the Z-score model is efficient in predicting bankruptcy and this augurs well with the need to examine the effectiveness of loan models.

Paliwal and Kumar (2009), however, criticised techniques used in the Credit Score model, such as Expert Systems and Neural Networks, observed as difficult to comprehend. Similarly, Abdou and Pointon (2011) pointed out that a specialist may be required to simplify or explain the outcome, with subjectivity, inconsistency and individual expert preferences possibly not being compatible. Furthermore, probit analysis, which analyses the relationship between a stimulus and the quantal (all or nothing) response, faces a high probability of incorrectness on the coefficients, due to a normal distribution effect. This makes the technique unreliable and impacts Credit Score model performance, thus causing incorrect future loan predictions (Abdou & Pointon 2011).

Additionally, Reece (2010) postulated there are non-financial or external factors that affect bank operations, which include economic, political, social, and legal, as well as technological, and environmental aspects, with these external factors beyond the bank's control. However, these factors need to be considered when lending and suggesting variables that should be weighed in the loan model. These factors are briefly discussed below.

Political factors: Havaladar (2010) argued that the political situation determines government policies for the business community and international trade challenges, with which Calomiris and Haber (2014) agree. Any negative policies, for example raising taxes that will increase product prices, should be accounted for in the loan model, as it threatens firm capacity to meet monthly obligations that may eventually result in poor quality loans on the loan book.

Economic factors: Some economic measures, such as interest rates and inflation impact loan performance (Fofack 2005; Kalu & Mike 2020). Raw material, labour, buildings, and other capital costs were argued as economy-related factors (Baines, Fill & Page 2011). Accordingly, some factors have an economic impact on economic activities, such as the financial arena, economic downturn or availability of financing

facilities. All these have the potential to lead to poor loan performance as they upset product demand, which is expected to generate cash flow.

Social factors: The bank keeps comprehensive track of social, cultural, and environmental changes; most importantly, household demographics, lifestyles and family structures and values in society (Baines *et al.* 2011). It is also known that radical change or any form of modification may lead to subdued product demand, which would consequently decrease anticipated cash flows that, in turn, impact loan repayment.

Technological factors: A proposition brought forward postulates that technological developments upset markets of existing products due to product innovations or new product development (Havaidar 2010). Furthermore, a bank takes cognisance of technological aspects when lending to its clients, and borrowers lagging in technology should be scored accordingly.

Legal factors: The legal element has been a critical factor, as every aspect of an organisation should be legally taken care of for enforcement and realisation of security (Baines *et al.* 2011). Any delays on legal matters may impact loan performance, especially where there are payment disputes from the borrower.

Environmental factors: Global environment changes emphasise that goods should meet certain standards to mitigate the destruction and pollution of the environment (Reece 2010). Financial institutions are required to abide by the regulators' directives to secure a reasonable market share. Furthermore, Commercial Banks consider funding corporate clients with environmental certificates that confirm their compliance. A bank may, for example, recall its facility when a client is not in compliance with environmental certification, which may result in some losses as facility tenure is cut short.

The above discussion indicates a raging discourse in the Zimbabwean financial institution and banking sector. Therefore, loan models must be used to minimise the risk of bankruptcy of borrowing clients in Commercial Banks. Some believe the Z-score, for example, is still very relevant and a useful loan model, while some disagree

and propose more modern models. While the argument persists, banks continue to suffer. This study thus seeks, against this background, to look into these models' effectiveness.

1.8 Research Aim

It is the primary aim of this study to seek to understand how LPMMs impact loan performance in the Commercial banks of Zimbabwe.

1.9 Overarching Research question

To unpack the study, this work was guided by the research aim, research questions and research hypotheses.

1.9.1 Main Research Question

To what extent and in what manner is loan performance of Zimbabwean Commercial Banks impacted by LPM Models?

1.9.2 Sub Research Questions

To delineate this question, the main question was split into five sub-research questions as follows:

- i. Which LPM Models are used in your bank to predict loan performance?
- ii. Which parameter attributes do the commercial banks in Zimbabwe consider in LPM model development?
- iii. What are the methods and means Zimbabwean commercial banks employ to measure effectiveness of a loan model as lending tool?
- iv. Does a loan model separate potential NPLs at evaluation stage?
- v. What influences a Commercial Bank to change its loan model or develop a model?

1.9.3 Research Hypotheses

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.

1.10 Theoretical Framework

This work focused on LPM and loan models, to determine the effectiveness of loan models under use by commercial banks in Zimbabwe. An eclectic synthesis, made up of social, economic and loan performance data, linked to portfolio management, as well as financial intermediation theory which was developed by Bhattacharya and Thakor (1993), who basically focused on risk management in banks and brokerage and asset transformation, respectively; prompt all activities of banks of this study to fall under financial intermediation. Additionally, other theorists, such as Hodgman (1960) offered guidance to banks on loan limits; Markowitz (1952) assisted with risk of return on investments (ROI), while Inderst and Mueller (2007) underlined the importance of collateral in credit granting. These theories will be discussed in chapter Three. For the study to build a theoretical framework, it examined how loan portfolios are supposed to perform and the manner in which credit risk theories infuse the way banks make final lending decisions, following the use of various loan models.

1.11 Objectives of the Study

- i. Establish whether LPM Models exist and are applied in Commercial Banks in Zimbabwe.
- ii. Examine the LPM Model parameter attributes currently used by Commercial Banks in Zimbabwe.
- iii. Analyse the effectiveness of LPM Models and loan performance in Zimbabwean Commercial Banks.
- iv. Assess the impact on loan performance by LPM Models in Zimbabwean Commercial Banks.

v. Identify circumstances that motivate Commercial Banks to enhance or develop an internal loan model.

1.12 Research Methodology

Taking the advice of Saunders, Lewis, and Thornhill (2016), a pragmatist philosophy was found most appropriate for the study, as it allows using a method of mixed research. As a result, both quantitative and qualitative data collection methods were adopted by the study. Adopting this mixed research method was based on its call to integrate diverse viewpoints, resulting in an enriched study relevant to a developing nation. This work thus adopted a sequential explanatory mixed-methods research design and both primary data from the source and secondary data from a review of literature were applied, which assisted in identifying the existing knowledge gap.

To collect quantitative data, a 5-point Likert Scale questionnaire was administered to participants, comprised of lending personnel in 15 banks that offer commercial banking services. One Building society and a Savings bank, whose licences and banking act allows them to conduct Commercial Banking business, were also included in the study. One Commercial bank that was not forthcoming was left out, resulting in a total of 14 Banks. A semi-structured interview was used to collect qualitative data from both practitioners of existing banks and closed banks. Data collected were analysed with the help of the Social Sciences Statistical package (SPSS) version 24.0, as well as Analysis of Moment Structures (AMOS) v 24.0, to yield descriptive and inferential statistics. To test the hypotheses, Structural Equation Modelling was performed (Covariance based) was opted due to large sample. The research process was also guided by ethical considerations.

1.13 Key Findings and Contribution to Knowledge

The key study findings are as follows: effective models yield quality assets achieved through robust parameters, input and/or variables, the features of a model make it effective, while mechanisms applied to measure efficiency of loan models are NPL ratios as well as the ratio of defaults to performing assets. Furthermore, loan models are found to have no social discrimination and they can predict risk better than by judgement from lending officers.

1.13.1 Contribution to Literature

To the best of my knowledge, this is the first study that has compared the effectiveness of all three loan models, these being the Credit Score; the Z-Score and the Asset-Based models, within Commercial Banks of Zimbabwe. In this comparison, the Credit Score model (corporate) turned out the best in assessing loan performance. Nevertheless, it is a model commonly used in banks because it meets bank requirements in identifying credit risks as addressed further on, in Chapter 3, 5 and 6. However, this is the first study that tested and confirmed the model's statistical power in mitigating risks, compared with the other two models. This would be a significant test for other developing countries.

Of particular significance, this study found parameter attributes of a model to be the strongest in accurately measuring its effectiveness. To strengthen the accuracy, the efficiency and effectiveness, only relevant variables must be incorporated as illustrated in the ensuing chapters.

The study has highlighted the pivotal role of loan models, pointing out that outdated loan models influence an uninformed decision, affecting loan performance. Therefore, the additional contribution to knowledge is a recommendation that loan model reviews should be ongoing, in line with the business environment, globalisation, technology and climate change, to remain relevant.

This work thus provides an insight into how an effective internal loan model can be developed in Commercial Banks, particularly in relation to a developing nation such as Zimbabwe. It has been demonstrated by the study that an effective loan model can be achieved; not by number of variables used but by relevant variables, which have a high significance in predicting feature defaults, as evidenced by a number of variables that were dropped during development of the model through a logistic regression (LR) technique, used in chapters three and five. Study successfully developed a loan model.

1.13.2 Methodological contribution

Studies that have examined the effectiveness of the models have focused largely on profitability of institutions using various methods. For example, Ajang (2018) used

regression analysis and found that screening clients, in addition to loan portfolio control, impacts profitability. Achimba (2018) also examined a single principal independent factor, namely the influence of management practices on loan performance. Also, previous studies (Abdou, Alam & Mulkeen 2014; Kanhukamwe 2015; Gumbo and Zoromedza 2016) used quantitative method, this study used a mixed research method and Structural Equation Modelling, applying four different dimensions with latent variables. Use of these multi-variables made this a more robust statistical technique that guaranteed high validity in measuring loan performance (Chapters 4 and 5).

1.13.3 Contribution to Theory

This work contributes to theory in the following manner; the credit risk theories, among them; credit rationing, portfolio theory and lender theory are mainly skewed towards borrower characteristics, overlooking other extrinsic factors. This work has therefore recommended need to modify the theories by incorporating other contextual factors and/ or external factors such as the macro environment and political environment variables (Chapter 5, 6 and 7).

1.14 Structure of the Thesis

This study is organised as follows:

Chapter One: Orientation and Overview of the Study

This chapter presented an overview of the study, research gap and contributions to knowledge, while it also introduced a brief literature review, the research problem, objectives, and questions, as well as the hypotheses and study rationale, among the major subsections.

Chapter Two: The Financial Architecture of Zimbabwe

The chapter provides the background to Zimbabwe's banking industry and how it has progressed, the country's economic outlook during the period under review, African financial systems, and the literature related to LPM. The reviewed existing literature largely comprises global scholarly studies.

Chapter Three: Loan Models

Chapter 3 discusses theories that underpin this work and related reviewed literature of the loan models under study. The chapter will highlight post model developments, presenting the advanced argument and measurement of loan model effectiveness.

Chapter Four: Research Methodology

In this chapter, the research methodology used in undertaking this study is presented. The methodology substantiates the adopted sampling strategy, the research design applied, data collection instrument, and measurement scales, among others. Quality measures such as research ethics, reliability and validity are also expounded.

Chapter Five: Empirical Study Findings

The chapter details the study findings, data analytical tools and techniques utilised, including the Cronbach's alpha, mean and standard deviations and factor analysis, in addition to confirmatory factor analysis and structural equations. This is followed by a discussion of the findings.

Chapter Six: Discussion of Findings

An analysis of the study results is provided in this chapter, in line with the research objectives, research questions and developed hypotheses. These results are deliberated relative to the literature reviewed in chapters 2 and 3.

Chapter Seven: Conclusions and Recommendations

This chapter offers conclusions on the study objectives, a summary of key findings and their contributions to knowledge, recommendations to banks and other stakeholders. Proposed future studies are given here.

1.15 Concluding Summary

A detailed account was presented in this chapter of the Zimbabwe banking challenges in the financial services sector, with a focus on high NPLs attributed to poor quality loans, hence bank failures. A brief literature review introduced the loan models under study (Credit Score, Z-Score and Asset-Based). The research significance was explained in terms of its aim to protect Commercial Banks through attaining quality loans. The chapter succinctly explained the failure of some loan

models to fully predict performance of a loan in its entire life cycle, thus resulting in NPLs. The chapter also indicated a step forward by the Regulator in establishing the Zimbabwe Asset Management Company (ZAMCO), whose main mandate is to 'mop up' commercial NPLs from various institutions. All the objectives, as shown in this chapter, are skewed towards efficiency and effectiveness of loan models. One of the main limits stated was prior studies being case studies, focused on a single model or institution.

CHAPTER TWO

THE FINANCIAL ARCHITECTURE OF ZIMBABWE

2.1 Introduction

This chapter provides a broad financial architecture of Zimbabwe, starting with the country's bank failures, by listing all failed banks; largely to demonstrate LPM challenges, as well as the weakness of some models. Secondly, economic revival efforts in Zimbabwe that reveal some solutions proposed by the regulator are examined, mainly to exhibit perennial bank unsoundness, with thirdly, an overview of the financial services structure in Zimbabwe, by presenting the evolution of the financial sector. The main reason was to demonstrate sector growth, as well as activities during pre- and post-independence. Fourthly, financial systems in Africa are investigated, which included but are not limited to the banking, insurance, microfinance, stock market and bond market sectors. This was meant to demonstrate and compare Zimbabwe with other financial markets in the continent and how it may impact loan performance; after which Zimbabwe's political economy background is provided. Further to this, the financial sector outlook is shown during pre- and post-independence, to validate the influence of politics or government policies on economic activities, such as bank performance. Lastly, the chapter will provide a review of empirical studies carried out that address LPM because the study aims to demonstrate gaps causing NPLs.

2.2 Zimbabwe Bank`s failures

The Great Depression of the 1920s resulted in many banks failing in the United States of America (USA), which encouraged experts in the finance sector to pay considerable attention to bank loan performance (McMillan 2014). The era, 1929 to 1932, witnessed a total closure of 2 859 banks in the USA. The country experienced further bank closures between 2007 and 2009, when 206 American commercial and savings institutions failed (Craig, Aubuchon & Wheelock 2010). In the case of the 1920s, several causes were cited for the USA's bank failures. They included Commercial Banks' participation in speculative activities; meltdown of stock prices; relaxed and highly flawed regulatory framework towards banks; and outstanding debts that continued to increase along with bankruptcy at banks secured by the stock

markets and the presence of NPLs from the agricultural sector, mainly caused by excessive international market prices and excess supplies of farm produce (McMillan 2014). During the crisis, many corporates scaled down their production costs by retrenching staff, which worsened their ability to service debts (Giuseppe & Postel-Vinay 2016).

Several African countries such as Kenya, Nigeria and South Africa (SA) have also suffered. In Kenya, banking problems occurred around 1986, culminating in 37 major bank failures by 1998 (Kithinji & Waweru 2007; Marshal 2017). These failures were caused by NPLs, attributed to insider lending, whereby funds were advanced to stakeholders of banking institutions such as employees, directors and shareholders, who failed to service the loans. Additionally, high NPLs illustrated that banks were not applying effective loan models, such as the Credit Score model, in the client vetting processes.

According to Dzomira (2014), SA had recorded many bank failures as well. The Reserve Bank of SA (2004) stated that due to NPLs and liquidity challenges, 22 banks exited the South African banking system between 1999 and 2003. Nigeria also suffered the same fate, as it recorded 21 bank failures between 1947 and 1952 and 25 banks almost collapsed in 2004 (Kupakuwana 2012). The observation was that light regulations, abuse of power, financial irresponsibility and direct criminal misconduct by bank directors of a younger generation caused these bank failures. Bordo and Landon-Lane (2010) argued this was sufficient evidence of a banking crisis.

In Zimbabwe, following post-independence (1980-1990), the country's banking challenges started in the year 1991 with the collapse of the bank formerly known as the Bank of Credit and Commerce of Zimbabwe (BCCZ) (Chigumira & Makochekanwa 2014). The Zimbabwean government had a 47 percent shareholding in this bank and was thus able to rescue the bank from complete closure through a capital injection; this led to a 100 percent increase in its shareholding, with the name of the bank amended to the Commercial Bank of Zimbabwe. The financial sustainability of the bank improved after the new capital injection, together with improved credit systems.

In 1995, a number of Zimbabwean banks experienced the same challenges as the Commercial Bank of Zimbabwe, including five other major banks, namely the First National Bank, Zimbank, Zimbabwe Building Society, and Universal Merchant, as well as United Merchant Bank (Mandizvidza 2011). In order to mitigate the impending catastrophic financial crisis in the banking sector at that time, Mandizvidza (2011) explained that the Zimbabwean government continued to bail out the Commercial Bank of Zimbabwe, as well as Zimbank and the Zimbabwe Building Society. However, some of the institutions that had not received a bailout continued to operate at a deficit. This situation proved to be unsustainable as the United Merchant Bank ended up closing in 1998, while Universal Merchant Bank closed in 2000 (Dzomira 2014).

Zimbabwe recorded a heavy financial blow between 2003 and 2004 as the Banking crisis cost the country up to Z\$140 billion. The RBZ highlighted that other financial companies that failed during this period included ENG Asset Management Company, National Discount House, Barbican Commercial Bank, and Rapid Discount House, as well as Century Discount House, Royal Commercial Bank, and Intermarket Banking Corporation, in addition to Trust Commercial Bank and Time Bank (RBZ 2004).

One of the notable challenges in the Zimbabwean economy and within its banking sector, was the depreciation in the value of its local currency against all foreign currencies (Hanke & Kwok 2009). The currency depreciated to such an extent it could not be used for any further transactions as of November 2008. In addition, hyper-inflation stood at 79.6 billion percent monthly rates (Hanke & Kwok 2009). In 2009, this prompted officially trading in a system using multiple -currencies, whereby American Dollars (USD) and the South African Rand (ZAR) were mainly used for all trading in the banks (RBZ 2009). The formidable challenges that surfaced during this time led to the need to also examine loan models.

Despite the stable currencies adopted, bank closures persisted. Some Commercial Banks continued to experience the same difficulties faced earlier (RBZ 2010). For the second time, CFX Bank failed and in 2010, Interfin Bank acquired it, while in 2010, EcoBank also acquired Premier Banking Corporation (RBZ 2010). In 2011,

Renaissance Merchant Bank was placed under curatorship and taken over by the National Social Security Authority (NSSA) in 2012 and rebranded to First Capital before its closure (Mabvure *et al.* 2012). Trust Bank and Royal Bank, which had both been relicensed, failed for the second time in 2012 and 2013, respectively. In 2015, Allied Bank and Afrasia Bank also voluntarily surrendered their licences and closed (RBZ 2015).

A massive decrease in several operating banks ensued. As of 31 December 2014, the number of operating banks in the country had been reduced from 29 to 19 (RBZ 2014). According to Mandizvidza (2011), the bank failures, which date back to the 1990s, were a result of liquidity and insolvency challenges, as well as NPLs, attributed to excessive lending and inadequate loan assessment methods, such as loan models. This demonstrated the importance of monitoring lending practices and loan performance. Chikoko *et al.* (2012) found bank failures were indeed caused by NPLs, influenced by incorrect analysis of credit applicants. Instead of using credit analysis tools such as the Credit Score model, banks placed much importance on security when extending credit.

Dzomira (2014) further cited the following reasons as causes of bank failures: intense competition that impacted the market share of most banks; inflation that resulted in declining revenues of borrowers and inability to service their loans; the RBZ's withdrawal of its function as a last resort lender; and putting liquidity pressure on some institutions, as well as poor corporate governance. Moreover, lack of adequate skills in lending departments was found to have contributed immensely to uninformed decisions being made and loans being granted, even to defaulters.

In the view of Kohli (2013), most bank failures were because of financial institutions' digression from regulatory requirements, such as minimum capital adequacy and international best practices, while standards of a non-performing ratio of less than five percent were also not complied with. Furthermore, it was found that failed banks lacked sound risk management principles and tools, such as loan models. Additionally, it was established that some banks did not have sound origination methods, suggesting the absence of loan models to assess applicants and

administration mechanisms; poor board oversight; poor management practices; and laxity in loan policies.

Scholars, such as Clair (1992), who assessed NPLs in various African countries, observed that many banks have been decreasing cut-off scores on their loan models or underwriting standards to temporarily increase their loan books, even though such actions result in NPLs. According to Kane and Rice (2001), lack of portfolio diversification causes NPLs, while Salas and Saurina (2002) opined that the macro-economic environment, such as when a country's GDP is negative, results in borrowers failing to service their debts. Louzis, Vouldis and Metaxas (2012) established that when loans are not evaluated properly but extended on dubious political grounds, they do not perform. This overwhelming consensus from analysts suggests African bank regulators should be more accountable to their banking industries and the need to use credit tools, such as loan models for individual banks, is emphasised (Calomiris and Haber 2014).

This study sought to specifically uncover the underlying influence of existing loan models or LPM Models on loan performance in Commercial Banks of Zimbabwe, in particular, commercial loans that loan large amounts to their corporate clients, exposing the bank to credit risk; while also determining the reasons that influence banks to adopt a new model or enhance an existing model and to test relationships between certain factors applicable to loan models.

2.3 Economic revival efforts through Banks in Zimbabwe

The RBZ (2009) has recorded that since the year 2000, Zimbabwe has been going through various economic challenges, with banks facing operational challenges because of existing and consistent economic hardships. To alleviate these challenges, the government has employed several strategies through the Central Bank.

From 1991 the Zimbabwean government began introducing the financial liberalisation of the banking sector (Harvey 1998). Roland (2008) defined financial liberalisation as a process of eliminating existing repressive strategies such as interest rate limits and direct credits by the authorities. The financial liberalisation

increased the depth as well as the width in the Zimbabwean banking sector, meaning that more banking products were then available at various geographical locations than previously represented by any bank. Additionally, it also removed barriers to enter business as a financial institution. Thus, although the sector was previously dominated by foreign banks, including Standard Chartered, Barclays and Stanbic, with the Commercial Bank of Zimbabwe and Zimbank as local institutions, new players came on board. Furthermore, there was no direct lending by the regulator and the practice of modern credit risk was to be exercised by ensuring banks implemented best practices in credit analysis, such as the use of loan models.

Financial liberalisation was also institutionalised, for example, competition in the banking sector, resulting in many service providers' liberally marketing and promoting incentives to their clients. These included several choices of places to obtain best service from, therefore, improved efficiency, resulting in improved service delivery. Furthermore, this competition meant those who failed to meet client demands would potentially force clients to the next service provider or bank. Simultaneously, these benefits of liberalisation have aided allocation, balance and diversity of market force resources. In this way, bank activities could thus largely be determined by customer specific requirements. Failure to maintain such requirements might lead to a sharp decline of bank customers and or losing them to competitors (Roland 2008).

Liberalisation also saw domestic entities being integrated into global markets to influence better business practices, as well as implementing a sound monetary policy environment. Essentially, financial inclusion improved as new banks spread across all geographical areas in the country. Moreover, the practice of modern credit risk, such as loan models that can mitigate NPLs, was implemented.

Sadly, the financial liberalisation process did not yield the desired results. Instead, these measures led to numerous bank closures in the 90s, attributed to competition in the form of relaxation of credit standards to attract customers. The new relaxed measures inadvertently suggested they were not making use of loan model results. These financial institutions ended up granting loans to "unbankable" projects that then turned into NPLs (Makoni 2010).

Faced with liquidity challenges, inadequate risk management, non-disclosure of losses to the RBZ and high levels of NPLs, among a confluence of factors, the RBZ introduced the Troubled Bank Fund Act in 2004 (RBZ 2004). The modus operandi entailed that Commercial Banks could access bridging funding from the RBZ. The Reserve Bank would provide relief on their cash flow constraints while they developed sustainable internal strategies; including the enhancement of credit risk management tools such as loan models. The loan models were to be strengthened through technology, as well as updating variables, especially on the Internal Credit Score model. Basel i was also implemented to safeguard bank assets; that is, all the banks were to meet minimum capital requirements as stipulated by the regulator.

The liquidity challenge remained a perennial problem because banks failed to repay the RBZ timeously. The view of the International Monetary Fund (IMF) (2005) was that the liquidity support of more than two trillion Z\$ from the RBZ was insufficient to address the liquidity gap challenges the banks were faced with. This happened despite the relaxed repayment timeframe, which ranged between 30 to 90 days. As a result, nine institutions were placed under curatorship, while three of the banks were liquidated (IMF 2005). Furthermore, failure to achieve the desired results from the above interventions forced the RBZ to introduce the Troubled Bank Resolution Framework (TBRF) in 2005, with the objective to enhance systems in the banking sector by promoting international best banking practices.

The framework triggered the implementation of Basel ii, which ensured allocation of capital to all identified risks and guaranteed lasting solutions in rescuing unstable banks. Technical Guidance on the Basel ii implementation framework was provided to all banks and the procedures to be followed outlined. The regulator's supervision unit strictly monitored banks to identify weak systems that did not meet international standards. The standard referred to included compulsory use of loan models such as Credit Score, Z-Score and Asset-Based Lending for evaluating loans. During this intervention, it was the duty of the regulator to make recommendations before a bank was placed under curatorship. Despite all this effort, the banks continued to fail in the years 2010/2011.

The regulator further introduced another intervention, the Troubled and Insolvent Bank Resolution Policy (TIBR/policy) that came into effect in 2011, with some assistance from the IMF (RBZ 2011). The main objective of the policy was to assist the regulator on timeous identification, rehabilitation and amicable resolution of banks facing challenges. The policy also provided a framework that fostered consistency and cost effectiveness, in addition to transparent and timeous problem resolution principles as a guide for troubled banking institutions. This policy empowered the RBZ to take measures to stop a bank from declaring any dividends. The RBZ would embark in frequent on-site examinations, which would give them an opportunity to review the impact of the loan models on the loan book, as well as suspension of management fees and imposition of reports. The policy was designed to militate against poor asset quality and to guard against bank failures. It was also meant to ensure that non-compliant banks exit the sector with minimal disruption to the financial services industry.

Amongst a cocktail of measures to improve loan portfolio quality, the Regulator also established a special purpose vehicle company, known as the ZAMCO in July 2014 (RBZ 2015). The intention was to support the mandate of buying non-performing commercial loans which were secured from banks at a discounted rate. This was done with a view of collecting outstanding debts formally owed to Commercial Banks over time. Since its inception, the company has acquired bad loans of up to one billion Zimbabwe Dollars from the Commercial Banks. In that way it unlocked money to productive sectors with the objective of providing banks with liquidity and ensuring they grow their loan books with quality assets and mitigate the disruption of the banking system (RBZ 2018).

A private credit bureau and credit registry or databank with records of defaults and current loans running were also maintained within the RBZ to curtail multi-banked clients who were likely to cause NPLs. The fear was that this would eventually negatively impact bank capital and consequently cause bank failures (RBZ 2015). At any given time, players in the banking sector were able to confirm whether a prospective borrower had borrowed elsewhere, with the outcome then guiding the lender in their choice to join the funders for the given project. Loans from other institutions were also weighed in the loan model, thereby influencing the final cut-off

Score that determined client capacity to service debt. Essentially, the use of a credit registry and a loan model, such as the Credit Score model, could be of tremendous assistance to the bank in making an informed decision.

2.4 Overview of Financial Services Structure and Economy in Zimbabwe

Financial services in Zimbabwe have been evolving since pre- independence to date, with most developments underpinned by economic activities as well as the existing political environment (Hanke 2008; Calomiris and Haber 2014).

2.4.1 Financial sector: Pre-Independence (1979)

Foreign banks started operating in Zimbabwe (formerly known as Rhodesia) as early as the eighteenth century; that is, in 1892 and the bank's foundations are in England (Hanke 2008; Crush & Tevera 2010). Meanwhile, banking requirements in the country were made available by only two commercial banks that opened their doors in 1892 and 1895, respectively, namely, Standard Chartered Bank and Banks of Africa (Barclays). In addition, the financial system further developed in 1896 when a stock exchange was opened, followed by the establishment of Rhobank (1951); Grindlays Bank (1953) and the Central Bank (regulator) in 1956 (United Nations 1980a, 1980b, 1980c).

According to Hanke (2008), Zimbabwe had free banking since 1892, which means banks were not under special regulations and Commercial Banks were issuing own currency in the form of bank notes when the first bank was formed, however, in 1940, this method was replaced with a currency board. The system was abandoned because the government desired to benefit from the issuance of notes. Hanke argues that Zimbabwe's decision to leave the currency board system that had existed since 1940 and replace it with a central bank while it was a member of the Federation of Rhodesia and Nyasaland (1953–1963) was incorrect. He argues that a currency-board system would have resulted in lower inflation and higher economic growth than a central bank regime. Financial deepening, on the other hand, made substantial progress after 1963, with the financial-deepening ratio reaching 35 percent by 1980 (Kaseke & Charira 2012).

2.4.2 Evolution of the Financial Architecture

At the time of independence in 1980, the Zimbabwean government inherited one of the strongest banking systems in Africa outside of SA, at a time when the mainly black populace felt excluded from modern services, including credit (Harvey 1998). In the early 1990s, the government deregulated the banking industry, resulting in the establishment of black-owned financial institutions to compete with conventional institutions. Notable institutions were; discount houses, finance houses, commercial banks, and development financial institutions, as well as merchant banks, while resource mobilisation was also employed by the stock exchange (Carmody 1998; Kanyenze *et al.* 2011).

Importantly, the rivalry was largely centred on merchant banks, which brought together several skilled local bankers, including National Merchant Bank (NMB), Trust Merchant Bank (TMB), Universal Merchant Banking (UMB) and United Merchant Bank (UMB). The first indigenous commercial bank, the First Banking Corporation (FBC), was licensed in 1997, which increased the number of commercial banks to six from the traditional five, ANZ Grindlays (now Stanbic), Barclays, the Bank of Credit and Commerce International (now the Commercial Bank of Zimbabwe - CBZ), and Standard Chartered, along with Zimbank (Carmody 1998; Kanyenze *et al.* 2011).

2.4.3 Dominance of Commercial Banks

Zimbabwe financial services (Table 2.1), as with many other SSA countries, is largely dominated by commercial banks (UN 1980a; RBZ 2018). Furthermore, there used to be other financial service providers, for example, discount as well as finance houses, and merchant banks, which have either closed or were converted to Commercial Banks.

Table 2.1: Bank types

Institution Type	Number in 1980	Number in 2000	Number in 2018
Building Societies	2	5	5
Commercial Banks	5	15	13
Discount houses	0	7	0
Finance houses	0	7	0
Merchant Banks	2	6	0
Savings Bank	1	1	1
Total Banking Institutions	10	41	19

Sources: UN (1980a); RBZ (2018)

The banking sector was largely dominated by commercial banks at independence, as alluded earlier, commercial banking services were offered by banks such as: 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 (United Nations 1980a, 1980b, 1980c). Furthermore, these commercial banks complemented 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.

Meanwhile, failure of the Economic Structural Adjustment Programme of 1991 to yield desired results such as economic growth, low cost of funding impacted functions or activities of merchant banks, discount houses and finance houses which motivated these institutions to convert their licences to commercial banks. Examples include Kingdom (formerly Merchant bank and Discount house), NMB Bank and Trust bank that converted their licences to commercial banks, which facilitated access of cheaper deposits for on-lending. Furthermore, argumentation of financial services was due to the Bureaux de Changes, which came into being in 1994 (Africa Development Bank 1997).

All the merchant banks with existing sister companies as commercial banks, such as Barclays bank and Standard Chartered bank, become part of their existing corporate banking units which largely focus on commercial loans. Therefore, previously used lending technologies were discarded, as they now mainly focused on for example, vanilla lending, as opposed to asset backed loans or lease finance. On the one hand, this new development further strengthened commercial bank activities and dominance, as argued by the African Development Bank (AfDB 1997). On the other hand, commercial bank resource mobilisation stood at 46 percent (1987-1990); Post Office savings at 20 percent, while merchant banks prior to closure and building societies, respectively stood at 6 and 7 percent.

2.4.4 The Financial Sector during the independence era

From the 1960s through the 1980s, government control of banks in most developing nations was regarded as crucial, with the primary motivation for this policy approach

the desire of governments to control the path of credit in order to stimulate growth, which proved elusive (Harvey 1998). In 1980, Zimbabwe had four commercial banks, all of which were foreign owned (United Nations 1980a, 1980b, 1980c; Allen, Otchere & Senbet 2011). Further, other independent African countries responded to this apparent oddity by nationalising foreign banks, although this had a negative influence on the growth of the financial system. After witnessing the devastating effects of bank nationalisation in other African nations, the Zimbabwean government was wary of becoming involved in the financial sector, shunning the nationalising of banks (Mhlanga 2013).

Abel and Le Roux (2016) argued that by the time Zimbabwe gained independence in 1980, development opinion had changed from government controlling financial markets toward policies that were more market-oriented. Furthermore, other SSA countries, specifically Mozambique and Tanzania, have shown when commercial banks are owned by the state, this is not a guarantee of a noteworthy savings increase, with resources flowing to those economic sectors expected to contribute to growth. In 1980, the Government was offered expert advice, recommending participation in the financial sector by the State would be easier and more successful should it establish banks of its own to contend with banks that are foreign-owned.

In addition to regulations in foreign exchange to prevent cash obtained in Zimbabwe being moved overseas by foreign-owned banks, this structure was considered more successful than either nationalisation or taking control of foreign-owned banks (Chigumira 2000). The thinking was that all banks would be regulated by the Central Bank in order to guarantee credit was available for investment activity sectors deemed critical by the State to economic growth. Control of the financial system, as opposed to ownership, was viewed as the best means of mobilisation and fund allocation to investments that were productive (Chigumira 2000).

The government, in 1980, bought a major share (62 percent) of a subsidiary of the Netherlands Bank of SA (NEDBANK), namely RHODBANK, changing its name to Zimbabwe Banking Corporation (ZIMBANK). The change was brought about by the exit of NEDBANK from the financial industry in Zimbabwe, as well as the government's aim to preserve trust in its banking system. The stake held in ZB

Financial Holdings Limited by the government had been cut to 49.6 percent by 1993, with ZIMBANK owning 100 percent of ZBFH (the symbol traded under on the Zimbabwe Stock Exchange) (FINHOLD 1992/1993).

The government also purchased shares in the only financial institution that accepts deposits or Commercial Bank) of Zimbabwe, established in the 1980s. According to Harvey (1998), this nationalisation was unintentional although it was in keeping with the de facto strategy of the government, of using the Industrial Development Corporation (IDC) to purchase failing businesses, thus, averting closure and saving jobs. This involved supporting the soundness of the financial system as well as its credibility. The CBZ became profitable after significant restructuring and a Nominee company being formed to manage its bad loan book, and, since the late 1990s it has continued to be one of the major commercial banks in Zimbabwe.

2.4.5 Zimbabwe Economic Disintegration (1990s)

Zimbabwe, following large deficits on budgets and as well as on balance of payments embarked on Economic Structural Adjustment Program in 1991 which was financed by African Development Bank and World Bank (Africa Development Bank 1997; Richardson 2005; Brett 2005). The programme's main aim was to develop efficiency in all sectors that would result in growth of the economy; this however failed. Furthermore, following the poor performance of the programme, macroeconomic fundamentals and environment respectively failed and become unstable as evidenced by hyperinflation, consequently, loss of foreign direct investment and poor economic performance.

The weak economic performance also impacted bank loan performance, for example, to divest itself of its NPLs, a book of non-performing debts was sold in 1996 to a different company (Climax Investments) by Zimbabwe Financial Holdings (FINHOLD 1996; ZSE 1997). The majority of NPLs resulted from commercial bank lending activity (ZIMBANK 1996). To manage the non-performing assets portfolio of the Commercial Bank of Zimbabwe, a nominee business was established in the same way. Several RBZ annual reports have addressed the issue of non-performing assets (RBZ 2009), while the NPLs also suggest weakness of loan models.

The major causes of the build-up of NPLs have been highlighted as rush investment decisions, suggesting inadequate use of loan models and increased competition in the banking sector. Most banks' profitability has been lowered while margins have been stretched by deteriorating asset quality and growing competition from newly created banks. For example, there was a 25.5 percent decrease in average net margins (the percentage of net interest revenue to total interest income) in 1994, to a 1995 decrease of 14.2 percent and 11.6 percent in 1996 (RBZ 1998).

Furthermore, during the period under review, most businesses downsized or closed, resulting in significant employment losses and concerns regarding impending manufacturing sector de-industrialisation, associated with excessive costs of borrowing (Ndelela 1998; Moyo 1998). Between 1990 and 1992, 29 enterprises were liquidated; for the period 1990 to the first quarter of 1995, 1,273 companies were struck from the Company Register, while 1992 saw de-registration of 564 companies (Central Statistics 1998). However, financial liberalisation outcomes did not match the aimed for increase in investment and economic growth. Therefore, these reasons, together with the rising level of economic uncertainty, prompted a shift from long- to short-term maturities by banks in their loan portfolio.

2.4.6. The crisis period of the 2000s

The land reform programme of 2000, which aimed at shifting farm land ownership from the white minority to the local black communities of Zimbabwe, significantly contributed to the economic challenges faced by the nation (Koech 2011). This development influenced the overall decline in commercial production, amplified by an estimated 50 percent decline in the agricultural sector between the years 2000 and 2009. Corporates who had borrowed from commercial banks were incapacitated to generate sufficient cash flows to service their debts, resulting in defaults on loan instalments. The land reform programme evidenced some of the weaknesses of the loan models, thus they could not predict future political instability and social unrest, which all upset cashflows, hence, failure by borrowers to service their debts.

The change of Governors of the RBZ in the year 2003 saw the incoming Governor engaging in several quasi-fiscal activities like providing farm implements to the newly resettled farmers (RBZ 2003). Furthermore, this period witnessed bank closures, as

well as placement under curatorship by the regulator; hyperinflation and massive economic downturn; while GDP went down by an estimated 40 percent. Meanwhile banks were utilising depositors' funds without their concern for speculative activities among them purchase of vehicles, bricks and properties which they argued as preserve measure of capital. The regulator (RBZ) promptly reacted by cancelling its duty of last lender and introduced drastic measures in the form of the Troubled Bank Resolution Framework (TBRF) in 2005 (Makoni 2010). The prevailing banking sector challenges, however, impacted stakeholder confidence, including that of the general public; therefore, the banking public were now more comfortable in keeping their funds at home and offices (Kanyenze *et al.* 2011).

The economy, however, started to stabilise in 2009, following formation of the government of national unity, commonly referred to as the Global Political Agreement (STERP 2009). After a decade of monetary and financial disorder, the local currency was abandoned in an attempt to halt the serious disruption at macroeconomic level and restore its stability. The policy managed to stem the incapacitating effects of hyperinflation and the decline of the economy. Moreover, there was a sharp decline in inflation, which for most parts of the years 2014 and 2015 fell to below two percent, and then declined further into negative territory (ZIMSTAT 2015). Furthermore, Commercial Banks started to seek some lines of credit, notably from regional banks such as Afreximbank, which funded ZETRAF to the value of USD70million.

2.4.7 Financial Services Outlook in 2019

As at 2019, the RBZ (2019) reported that the structure of Zimbabwean financial services comprised at least 13 Commercial Banks, not less than five Building Societies, only one Savings Bank, as well as two Developmental Financial Institutions. It was further reported that the closure of the Merchant Banks and Discount houses was attributed to poor quality loans that created liquidity challenges; these institutions could thus not continue to create and maintain sustainable loan portfolios. Other institutions include the 204 credit-only microfinance institutions, while there are six deposit-taking microfinance institutions, with their target market mainly individuals and Small and Medium Enterprises (SMEs).

Products on offer by these banks include revolving credit, documentary credit and both short- and long-term loans. Corporate or business loans for companies, which are the subject of this study, are mostly offered to the manufacturing, agricultural, and services sector, such as tourism, mining, distribution, and communication, as well as the construction sector. Funding is used to capacitate borrowers; funds are used for working capital purposes or capital expenditure (RBZ 2018).

2.4.8 Banking sector's capital adequacy requirement

Caggiano and Calice (2011) agreed banks that have higher buffers of capital and liquidity can, in bad times, provide better support to businesses and households, such as when NPLs are high. These buffers capacitate banks to take up losses and during a downturn, support and sustain lending. Regulatory capital is perceived to be a safeguard against financial failure and it thus limits financial distress costs. RBZ (2014) confirmed that undercapitalised banks burdened by NPLs make it imperative for full capitalisation of an institution. As of 2019, minimum capital requirements of banks were as follows: Commercial banks USD100million; Building societies USD80million and Microfinance USD5 million, with operational banks that satisfied the regulator with this requirement (RBZ 2019).

2.5 Financial Systems in Africa

All banking systems in a financial system are herein discussed and what makes up an Africa financial system. Zimbabwe is an African nation, requiring assessment and comparison with other regional countries on whether the country has fully developed its financial system and how regional financial service structures impact credit allocation. For example, Kenya liberalised its banking sector in the 1970s, 1980s and 1990s, which improved its efficiency, suggesting loan quality is also a contributing factor (Kapaya 2019). Furthermore, regulation of the sector has resulted in banks not assuming big risks that impact LPM; a lesson for Zimbabwean banks to learn. The discussion on financial systems in Africa also demonstrates financial market participants, dominating institutions, as well as ownership of banks on the continent, business activities or transactions they offer and how these may impact loan performance. Therefore, banking systems in Africa will be fully explored, along with a discussion on microfinance, the insurance sector; stock market; and derivative

markets; as well as bond markets, whose activities complement Commercial Banks activities.

2.5.1 Banking Systems

In Africa, Central Banks and deposit-taking institutions comprise the financial system (Mehrotra & Yetman 2015). Additionally, Central Banks are nominally independent of political authority, yet, they collaborate with their respective states' Ministries of Finance to assist in creating and implementing the macroeconomic policies of individual governments. Furthermore, deposit-taking institutions are comprised of local banks, as well as international bank branches or their subsidiaries. Foreign banks have been a key part of African banking growth, with their proportion of total African banking increasing significantly over time. This growth may be ascribed to reforms in the financial sector these nations implemented, which resulted in the opening of African markets and the subsequent entry of international banks (Puatwoe & Piabuo 2017).

In most nations, banks that are state-owned or a limited number of big, sometimes foreign financial institutions, dominate the banking sector; in Algeria, for example, more than 90 percent of all banking deposits and assets are controlled by state-owned banks (Lassoued, Sassi & Attia 2016). However, as part of the restructuring agenda of African nations, the continent's banking industry is undertaking reforms that focus on types of restructuring of state-owned banks, such as privatisation, in order to improve the quality of financial institutions. This suggests improvement of Commercial Banks in Africa, on the one hand, in all aspects of their operations, including loan evaluations using modern tools, such as models to only lend to creditworthy clients.

On the other hand, a typical characteristic of the African banking system is that many banks invest in government assets, particularly treasury bills (Lassoued *et al.* 2016). However, this is troubling because it reflects a severely dysfunctional banking intermediation that prefers to provide safer government assets instead of private lending (Moyo *et al.* 2014). The low financial development level, with regard to private loan provision, is the outcome. This financial intermediation dysfunctionality is becoming more widely acknowledged in African policy circles, with several ongoing

efforts to create an environment in which banks can build information capital and function as informed agents, which are both critical for efficient resource allocation (Asongu & Odhiambo 2019). In Nigeria, as well as Malawi, Botswana, SA, and the Seychelles, banking systems are, nonetheless, active and reasonably well capitalised, with innovative banking practices pursued that allow using loan models, hence low NPLs (Chikalipah & Makina 2019).

Arguments from Beck and Hesse (2009), as well as Allen *et al.* (2011), are that there are mainly three categories of Commercial Banks ownership in Africa, namely big international institutions such as Barclays bank and Standard Chartered Bank, regional banks such as Ecobank and Standard Bank of SA (which trades as Stanbic in other countries) and Local banks or Indigenous banks in Zimbabwe, such as FBC Bank and Metropolitan bank. Furthermore, international, and regional banks are considered bigger, however, this is contrary to Zimbabwe's situation, wherein local banks are much bigger in size compared to foreign banks in terms of asset base, deposits, balance sheet size and branch network (RBZ 2018). Notwithstanding their strong liquidity position, international banks are very conservative on growing assets, as their low loan to deposit ratios demonstrated, compared to other banks (Nissanke 2001; Mugizi, Ndanshau & Aikaeli 2009; Andrianova *et al.* 2010). Furthermore, poised moral hazard, as well as lower adverse selection loan growth in Africa in comparison to developed nations are largely a result of uncertainty and or fear of defaults. This argues well for Commercial Banks to make use of loan models and mitigate poor quality loans.

Although the majority of countries were impacted as a result of the recent financial crises, the AfDB argues that the low level of Africa's financial integration ensured relatively insulation to African economies from the direct effects of the financial crisis, in part due to the financial markets' underdeveloped nature (Magombeyi & Odhiambo 2017). These assertions reinforce the need to validate loan models and LPM in Africa.

In Zimbabwe, the RBZ's principal objective is to maintain the Zimbabwean currency's internal and external value (Watambwa 2021). In this sense, the Bank oversees monetary policy formulation and enforcement meant to maintain low and stable

inflation levels. Exchange controls have gradually been liberalised as part of the wider macroeconomic reform programme implemented in 1991, with dealers approved to serve as the country's foreign exchange resource custodians since 1994 (Watambwa 2021). Zimbabwe's political difficulties have impacted every aspect of the country's society including banks, impacting loan performance (Calomiris and Haber 2014; Makoni 2014).

2.5.2 Microfinance

In Africa, these small financial enterprises have effectively provided financial services to those otherwise unable to obtain loans from either Commercial Banks or other financial institutions (Quaye *et al.* 2014). For this reason, micro finance institutions (MFIs) have gained popularity in this sector, with many individuals lacking assets of significance as backing to their loans, they neither require extensive loans, nor do they have savings accounts; aspects that banks pursue. In recent years, the sector has rapidly expanded, becoming a significant driver in African economies' development, while it is also a financial instrument at grassroots level (Diao, McMillan & Rodrik 2019). In addition, with access to financing for small businesses a major issue in Africa, the development of microfinance organizations (MFIs) has the backing of governments. In Africa, countries such as Ghana and Mozambique, are seeing rapid expansion in both rural and urban MFI (Sackeyfio 2021). However, MFIs do not have capacity to lend commercial loans due to low capital, leaving the gap to Commercial Banks.

2.5.3 Insurance Sector

Africa's insurance sector is still in its infancy and undeveloped in comparison to other developed nations (Landry & Johnson 2020). Property, car, health, and life, as well as casualty, and other forms of insurance are offered by insurance firms; nevertheless, the auto insurance sector in most nations dominates the market. The insurance market in several nations comprises mostly non-life insurance, accounting for roughly 85 percent of industry premium, while life insurance accounts for a small percentage of the market, yet, it is the fastest expanding area in the insurance industry (Chikalipah & Makina 2019). For example, there is a sizable insurance industry in Nigeria and as of 2008, 48 companies operate in insurance (Azutoru, Obinne & Chinelo 2017). Even though insurance firms in this sector are mainly

privatised, governments in several of these nations still own significant interests in the companies. Nevertheless, although insurance companies do not grant loans, they invest with some Commercial Banks, with these funds used for lending to bank customers after assessment, allowing these banks to dominate the market, especially in Zimbabwe.

2.5.4 Stock Market

A significant result of Africa's substantial financial sector reforms, which include legislative initiatives that reinforce capital markets, is the increased attentiveness to stock exchange construction, notably in SSA. There were just five stock exchanges in SSA and three in North Africa 20 years ago, yet, there are currently more than 20 in operation (Elamer *et al.* 2019). Except for the two oldest markets established in the 1880s in SA and Egypt, there has also been a boom in market capitalisation throughout Africa.

The Zimbabwe Stock Exchange (ZSE) is active and has been in existence since 1896, has welcomed international investment since 1993 and comprises a few dozen members, with more than 65 listed securities (Raubenheimer 2019; ZSE 1999). The country's two indices, the Zimbabwe Industrial and Zimbabwe Mining Indices, as well as individuals who bring funds into the country by means of a licensed Commercial Bank, are now able to send their income and sale proceeds back without being taxed, although dividends and capital gains are taxed at 15 and 10 percent, respectively (Mukwembi 2018). Commercial Banks, therefore, remain central on any business transactions.

2.5.5 Derivative Markets

Other than the SA markets, Africa's derivative market only came into existence a few years ago (Flint, Seymour & Chikurunhe 2018). However, due to certain governments in Southern Africa and the regional exchange in French West Africa imposing measures, the WAEMU zone derivative market is very young; whilst Southern Africa's market (Namibia, Botswana, Seychelles and SA) flourishes (Claessens & Van Horen 2015). Nevertheless, foreign currency futures with modest liquidity and maturities ranging from three to six months are available in West Africa. In addition, derivatives business in Botswana mostly comprises foreign exchange futures traded

over-the-counter and swaps of currency (Chidaushe 2019). This suggests markets can also provide liquidity to Commercial Banks to on-lend.

2.5.6 Bond Markets

Bonds can be referred to as small units issued by corporates as debt and are securitised so they can be tradeable assets, however, a major aspect of Africa's financial markets is its lack of bond markets for not only government but also business bonds (Oji 2015). Nigeria is the only Anglophone West African country that has a secondary debt market as well as a bond index (Mu, Stotsky, & Phelps 2013), with bonds issued by the Federal Government of Nigeria (FGN) and a range of three-to-20-year maturities that both primary and secondary markets offer. South African government bond issuance began in the 1980s, when the issue of bonds was done only on demand, while market trading, which started in 1996, piqued the interest of the public to where currently, the bond market turnover ratio can be rated against that of other mature markets (Turner 2012). In Botswana a primary dealership system exists for government bonds in both main and secondary markets. The Bank of Botswana manages primary bond offerings on behalf of the government in Botswana (Allen *et al.* 2011).

Zimbabwe issues Treasury bills with 91-, 182-, 365-, and 728-day maturities, as well as 2- and 3-year maturity treasury bonds (Allen *et al.* 2011). In 2005 the country issued a 5-year inflation-indexed bond, however, due to an unfavourable business environment, debt is not issued in the Zimbabwean bond market by private sector firms that prefer to borrow from Commercial Banks. Therefore, banks should have tools that can assess any company from different sectors.

2.6 Loan Portfolio Management

LPM refers to the process that manages and controls risks inherent in the credit process. Loan portfolio assessment for banks allows for a simple approach to examine systems step-by-step, along with the processes and guidelines that establish portfolio quality and deal with the actual portfolio sample, dispersed over financial institution branches (Abdus 2004). In addition, Gregoriou and Hoppe (2009) explained LPM as systematically paying detailed attention to a loan portfolio, such as

evaluating the risk or return profile of the loan portfolio and enhancing its soundness through monitoring.

Geek (2014) describes LPM as the process of developing a loan portfolio and managing the risks inherited in these loans. Furthermore, LPM aims to reduce defaults through monitoring. According to George *et al.* (2013), not only does the comparison of the existing portfolio management system to organisational guidelines and best practices that are internationally accepted bring out systemic inadequacies, it also reveals controls that are ineffective and the resulting risks in the processes. The main LPM factors are risk, return and monitoring, as explained below:

2.6.1 Risk

Els *et al.* (2010) and Madeira (2018) define risk as failure to achieve planned results, which inhibits business. This work therefore argued that every investment is exposed, hence the need to unpack the risks inherited at inception or during loan tenure, by putting mediatory mechanisms in place. Some risks associated with LPM are foreign exchange, commodity, country, and market risks, as well as settlement, concentration, and systemic risks.

Foreign Exchange Risk is where an investment or returns on such investments respond negatively to an unstable exchange rate (Els *et al.* 2010; Madeira 2018). For example, in Zimbabwe a client may obtain a loan in ZAR but when the currency starts to lose its value, the bank will record losses when other multi-currency starts to firm up. Therefore, it can be argued that the captioned risk is important in portfolio management because when the borrower uses a weaker currency to service their obligation, they may find it difficult and result in NPLs.

Commodity Risk is the interaction between business uncertainty and commodity price instability (Poitras 2015). The main setback from this risk is when prices diminish, when a borrowing client had already procured the commodity at a higher price, fails to recover costs and thereafter, fails to service the loan obligation, hence NPLs in a portfolio.

Country Risk is recognised by Els *et al.* (2010) as political risk, with Khaled and Wahabas (2019) who agree that investors pay attention to the prevailing political atmosphere and economic performance. These are fundamental to high production levels influencing positive cash flows that service loans. This risk exposes bank's loan portfolio, as a negative political environment impacts smooth operations of a business which will influence NPLs. It can be argued that there is need to reduce exposures to some business which are highly affected by politics and concentrate on others which are moderate for example retail business because even in war people still want to buy basic foods.

Market Risk refers to monetary losses attributed to instability in market prices, incorporating various instruments (Szylar 2014). Furthermore, market risk refers to losses to bank trading due to changes in equity, movements in interest rates, credit spread changes, and foreign exchange rate movements, as well as other price indications with values based on the public market. This work argued that it is important to have mitigation measures in place because any loss recorded will upset performance of the portfolio.

Settlement risk is defined by Garp (2007) as loss due to failure by the counterparty to either perform or liquidate the borrowings on the due date. Khaled and Wahab (2019) concur this risk arises immediately after releasing the money to the other party; for example, banks granting each other overnight accommodation or overnight loans to cover its day gap. The study argues on the imperativeness and adequate evaluation of clients followed by granting of appropriate limits to counterparts as their failure to perform will impact bank loan portfolio as well as liquidity position of the lender.

Concentration risk is wherein an institution's portfolio is skewed towards certain sectors or funds are extended to one client (Horcher 2005; Bolder 2018). Therefore, concentrated lending to one sector or client exposes the bank to any undesirable eventualities that impact repayment of debt; hence the importance of mitigating such a risk, which negatively impacts a loan portfolio.

Systemic risk refers to market changes or events that impact large market participants, thus slowing down expedition of banking transactions (Toit *et al.* 2010; Madeira 2018). A common source of this type of risk could be political unrest, such as mass protests, which interrupt operations of some borrowing clients, thus impeding cash flows that pay the debts. A portfolio may deteriorate if systemic challenges persist making it necessary to have a buffer position or capital which close a liquidity gap.

2.6.2 Return

Rate of return demonstrates and summarises the merits of a project driven by cash flows and not on rates offered elsewhere (Firer *et al.* 2012). Additionally, hurdle rate or the minimum acceptable rate of return, is the expected return rate by the investor and should be equal or greater than the bank's investment return. Further, a good return exhibit probability of loan performance which reduces NPLs in a portfolio.

Marx *et al.* (2017) highlighted return as a full benefit or detriment associated with an asset over a given period. The benefit is realised when an asset generates additional cash flows to the bank and may be determined annually as a percentage using this formula:

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

Where R can be described as the annual return; P_t is taken to be the price (value) of the asset at period t ; P_{t-1} denotes the actual price (value) of the asset at period $t-1$; C_t can be described as the net cash inflow received from the asset during the period $t-1$ to t (Marx *et al.* 2017).

2.6.3 Monitoring

Monitoring is the process of maintaining a relationship with the client and examining its performance and probability of fulfilling repayments as per agreement (Gregoriou & Hoppe 2009). Saleh, Alkasasbeh and Bader (2017) 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 & Lucey 2008). Ratio analysis requires statistically 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 (Megginson *et al.* 2008).

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

Liquidity ratios determine company capacity to meet short-term obligations (Megginson *et al.* 2008); examples are Current ratio calculated as $\text{Current assets} / \text{Current liabilities}$; 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 $\text{Current Assets} - \text{Stocks} / \text{Current Liabilities}$, 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.

Meggison *et al.* (2008) have, however, raised concerns regarding ratios, as far as the possibility exists 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), 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 & Hudgins 2010). Additionally, management of a loan portfolio is essential as it leads to safety of an institution due to quality loans making it imperative for a bank to have a skilled team management of the clients hence success management of clients demonstrates effectiveness of the loan model.

Brown and Moles (2014) argued that lenders proactively provide for anticipated losses attributed to non-performance of loans. The unforeseen circumstances of the business environment may force some of the clients out of business hence failing to service their loans as per agreed arrangement. The Zimbabwe banking regulator, RBZ, requires all lending institutions to provide for any remaining obligations to the banks (RBZ 2011). However, loans have to be rated first before provisioning, as per the RBZ (2011) classification (Table 2.2) below.

Table 2.2: Classification of Loans

Rating Classification	Sub-rating	Descriptive Classification	Risk Level	Five Tier Loan
1	-	Prime Grade	Insignificant	Pass
2	2a	Strong	Modest	Pass
	2b	Strong	Modest	Pass
	2c	Strong	Modest	Pass
3	3a	Satisfactory	Average	Pass
	3b	Satisfactory	Average	Pass
	3c	Satisfactory	Average	Pass
4	4a	Moderate	Acceptable	Special Mention
	4b	Moderate	Acceptable	Special Mention
	4c	Moderate	Acceptable	Special Mention
5	5a	Fair	Acceptable with care	Special Mention
	5b	Fair	Acceptable with care	Special Mention
	5c	Fair	Acceptable with care	Special Mention
6	6a	Speculative	Management Attention	Special Mention
	6b	Speculative	Management Attention	Special Mention
	6c	Speculative	Management Attention	Special Mention
7	7a	Highly speculative	Special attention	Special Mention
	7b	Highly speculative	Special attention	Special Mention
	7c	Highly speculative	Special attention	Special Mention
8	8a	Substandard	Vulnerable	Substandard
9		Doubtful	High Default	Doubtful
10		Loss	Bankrupt	Loss

Source; RBZ (2011)

According to RBZ (2011), all loans categorised from grades 1 to 7 are performing loans which enables commercial banks or any banking institutions to book income, thus interest being earned monthly. The regulator (RBZ), however, stipulates that all

loans classified from grades 8 to 10 are NPLs and no income is accounted on them. Therefore, according to most commercial banks annual reports (2011-2018) and key risk personnel, normal monitoring is applied to clients rated 1-7, close monitoring is required for all clients graded 8-9. Whilst accounts graded 10 are defaults and bank will try to find means of exiting the relationship and or considering for closure. The following (Table 2.3) is a rating scale system used by BancAbc:

Table 2.3: BancABC Internal Rating Scale

5 Tier	Descriptive Classification	Risk Level
Pass	Prime Grade	Insignificant
	Strong	Modest
	Satisfactory	Average
Special Mention	Moderate	Acceptable
	Fair	Acceptable with care
	Speculative	Management Attention
	Highly Speculative	Special Attention
Substandard	Substandard	Vulnerable
Doubtful	Doubtful	High Default
Loss	Loss	Bankrupt

Source: BancAbc Annual report (2016)

BankAbc's rating scale (Table 2.3) is mirrored to that of the regulator and serious asset quality concerns are largely at; substandard, doubtful and loss category suggesting calls for a more efficient system to save the relationship as well as generate some income before exiting the relationship.

Table 2.4: Provisioning of loans

Grade	Provisioning Percentage (of Exposure)
1 to 3	1%
4 to 5	5%
6 to 7	10%
8	20%
9	50%
10	100%

Source: RBZ (2011)

The above summary (Table 2.4) depicts that higher provisions are provided for clients with soaring ratings, implying a high probability of not recovering the borrowed funds. From grades eight to 10, wherein the bank effects provisions of between 20 to 100 percent, no accrued interest is considered due to the default status; this is extreme and the probability of losing funds is almost predictable, with write-off the last resort.

2.6.4 Loan Portfolio Management Effectiveness in Africa

George *et al.* (2013) argued that Kenyan banks' profitability was influenced by LPM effectiveness, implying borrowers were paying loans on time. This study sought to analyse whether profitability measures were associated with loan portfolio increments or decline, along with interest expense, administrative cost, and organisational level asset value. The study revealed that managing NPLs, provisions, as well as contingencies and bank operating expenses were imperative, hence, their success would improve bank performance. Notwithstanding other contributing factors to bank profitability and its determinants, the work proved that effective LPM results in profitability of an institution, suggesting there will be less or no bad debts written off. However, George *et al.* (2013) were not precise on the loan model used to evaluate and monitor loans prior to liquidation.

Magali (2014), argued that poor LPM as the cause of NPLs in Northern Tanzania as evidenced by an analysis of 496 loans from ABC rural Savings and Credit Cooperative Bank (SACCOS). The study aimed to determine effectiveness of LPM and the findings reveal that a loan book size had an influence on portfolio quality suggesting need to manage growth of a loan book. Whilst gender and geographical location of clients who borrow did not have much influence on loan portfolio

performance. Furthermore, the following mitigatory techniques were implored to manage credit risks and improve loan portfolio: collateral, portfolio diversification, referral letters from government offices as well as use of guarantors. Loan portfolio was also affected by unstable prices for agricultural clients hence need to establish future markets before season starts which would improve loan performance. To improve loan portfolio, the study recommended use of an effective software, writing off NPLs, improve loan repayments or collections efforts by a bank and appropriate loan classification. The study neither noted nor recommended any effective loan model for evaluation as well as monitoring to maintain a clean portfolio.

Ozili (2015) carried out a study extending the literature on the determinants of NPLs. The author investigated whether banks anticipate NPLs by adjusting balance sheet. Insights were drawn from credit risk management team and bank manager actions to curtail the size of NPLs. After an examination of 82 banks from the US, Europe, Africa and Asia, banks were found to adjust loan loss reserves and loan growth levels to diminish the number of NPLs, which led to loan portfolio improvement. The results do not show evidence that NPLs are minimized through loan diversification. In addition, Ozili (2015) discovered that in developing countries, when banks expect high NPLs, they reduce-loan growth, whereas in developed countries banks do not adjust loan growth in anticipating the level of NPL; thus, there is a need for a suitable strategy to enhance loan portfolio.

Post-crisis Basel regulations were not found by Ozili (2015) to result in a decreased size of NPLs among developed countries' banks but in some developing countries appear to minimize NPLs. Overall, the significance and predictive power of each bank-specific factor was concluded, excluding diversification of loans. In addition, in explaining NPLs, regulatory variable and macro-economic indicators depend less significantly on regional factors and more significantly on factors that are country-specific. The study did not specifically address or detail loan model effectiveness on managing a loan portfolio.

In their paper, Bhat, Tariq and Ahmed (2020) assessed the effectiveness of LPM for Ethiopian commercial banks. The research further assessed the challenges Ethiopian commercial banks are facing, with regards to the implementation of

effective LPM frameworks, as well as possible solutions. The research made use of a case study research focused on a selected number of commercial banks in Addis Ababa, the capital city of Ethiopia. The researchers collected both primary and secondary data through loan officers and management of the sample, as well as bulletins and published reports. From the research, Bhat *et al.* (2020) noted most commercial banks reduced their default risk through measures such as staff training, reviewing client history and diligently appraising submitted proposals, among others. The researchers equally noted that lack of follow-ups, once loans are disbursed, and lack of adequate assessment of client credit-worthiness, are among major contributors to the poor LPM by these banks.

Bhat *et al.* (2020) equally noted that lack of adequate data at national and micro-level regarding potential clients, as well as diversion of funds by customers from the use loans are applied for, were among major challenges commercial banks should address. It can be noted the researchers focused on LPM effectiveness from the perspective of already distributed loans, covering less ground regarding pro-active measures to pull customers with better credit worthiness, necessitating this study.

2.6.5 Loan Portfolio Management Effectiveness in Zimbabwe

Mavhiki, Mapetere and Mhonde (2012) undertook a study to evaluate credit management in Zimbabwe by focusing on challenges that impact loan portfolio performance. The study revealed that banks are exposed to high risk of failure through increased lending, with non-performing loan levels also on an upward trajectory, evidencing high probabilities of failure to collect all due payments as a result of depressed loan performance, thus, LPM of banks was not generating good results. The most outstanding recommendation by the study was the need for robust systems in credit management (risk), complemented by enhanced credit policies. However, the study did not outline some loan evaluation and monitoring techniques, such as loan model effectiveness.

Ngonyamo (2014) investigated the causes of NPLs in Zimbabwe and how banks may mitigate these, as they are a source of poor LPM and an indication of ineffectiveness, which impact loan performance. The major findings illustrate that NPLs are a result of: cheap imports of goods, with substitute products produced by a borrower who is

a local manufacturer, hence loss of market share; closure and or liquidation of companies that would have borrowed from the bank; loss of primary source of income especially individuals upon losing their jobs due to various reasons, among them retrenchment; along with cost (interest) of borrowing, which increases instalments, making it difficult to sustain by the borrower; weak credit appraisals by the bank, as well as insider loans.

Furthermore, both negative and positive relationships exist between causes and the level of NPLs. For example, the unemployment level and poor lending skills have a positive relationship with NPLs, while GDP growth has a negative relationship with NPLs. To improve LPM effectiveness, the study revealed use of debt collectors, information sharing by banks and monitoring of loans, among others. Findings from Ngonyamo's (2014) study, however, neither specified the actual tools used by banks, such as loan models, to evaluate and monitor loans, nor the reasons why NPLs are on the increase if these tools are effective; thus, a gap to be filled by the study.

Chambati (2018) employed a study on credit risk management and NPLs that also influence loan performance impact on microfinance in Zimbabwe. The key findings showed that NPLs could be reduced by, among others: booking only secured loans; having updated credit policies; thorough loan evaluation; and regular provisions to cover for potential defaulters. The study further revealed that notwithstanding small amounts advanced by microfinance, NPLs remained unabated, as with commercial banks. Therefore, loan portfolio management is not effective in the financial services industry. However, Chambati (2018) did not apprise suitable loan portfolio models that are effective and consequently reduce NPLs.

Comprised mostly of case studies, all the preceding work did not fully focus on commercial loans in all Commercial Banks in Zimbabwe, while some studies were undertaken in other regional countries such as Kenya, Tanzania and Ethiopia, where the business environment differs from Zimbabwe. Prior studies also concentrated on Commercial Banks' existing loans portfolio and not on loans portfolio management from the outset in the respective countries where studies were undertaken (Omar 2019). The manner in which loan models could impact the entire banking sector's loan portfolio management and loan performance were also not the focus of any of

these studies. Furthermore, the majority of previous studies were mainly underpinned by mitigatory measures of non-performance loans, with effective tools such as loan models excluded. Effectiveness measures of loan models were also not focused on in most studies, therefore, whether and in what manner they could influence the outlook of loan portfolio management and the entire banking sector's loan performance was not explored.

Previous studies also overlooked and or did not consider the following factors:

- the ages of existing loan models and their impact on LPM and or loan performance;
- details on whether the loan model used to evaluate an application can be used to monitor the same loans prior to liquidation;
- there were neither notes nor recommendations of any effective loan model for evaluation and monitoring to maintain a clean portfolio that a particular country favoured;
- the business environment was mostly ignored, for example, performance of the economy, complemented by the macro environment outlook, such as inflation and deflation rates, along with political outlook, among other factors; in addition to the outlook of loan books in the country and levels of NPLs.

Demonstration of the gap in knowledge is illustrated by the fact that, notwithstanding all existing current literature, the issue of NPLs through loan models and LPM, in Zimbabwe specifically, has not been fully addressed.

2.6.6 Reducing the knowledge gap

The knowledge gap, as explained in chapter 1, is supported by various scholars who have also undertaken studies to improve loan quality (Berger *et al.* 2005; Anderson 2007; Chuang & Lin 2009; Paleologo *et al.* 2010). Furthermore, the RBZ reflected bank failures and NPLs peaking at 20 percent, despite claims by banks on the use of loan models (RBZ 2015). Credit risk theories (chapter 3) such as credit rationing, portfolio theory and lender theory, and results (chapter 5), with the analysis of results and resulting arguments (chapter 6), shall be used to contribute towards knowledge; hence, reduction of the gap in knowledge is expected.

2.7 Concluding summary

The chapter provided an overview of the overall landscape of the African financial sector, as well as the development of the Zimbabwean financial sector. In addition, the chapter provided a synopsis of Zimbabwean banking sector architecture, highlighting foreign-owned bank dominance within the sector and the growing competition from MFIs within the lending business of banks. The chapter lastly provided a review of prior literature on LPM, while also indicating the gaps within previous studies regarding the application of loan models to improve loan portfolio.

CHAPTER THREE

LOAN MODELS

3.1 Introduction

This chapter analyses scholarly work on the loan models under study. The analysis critiques pertinent theories and models regarding their effectiveness in credit assessments and how they reduce NPLs. Credit evaluations through various loan models have seen global growth during the last three decades, largely because of the demand for credit on various banking products (Chen, Guo & Huang 2009; Banasik & Crook 2010). Products whose applications can be appraised using loan models include consumer loans (Lee & Chen 2005; Sustersic, Mramor, and Zupan 2009), credit card evaluations (Quah & Sriganesh 2008), small businesses (DeYoung *et al.* 2008) and mortgages (Haughwout, Peach & Tracy 2008).

The study is underpinned by Financial Intermediation theory and Credit Risk theories such as, credit rationing, portfolio, and lender-based theory. The analysis begins with financial intermediation theory, developed by Bhattacharya and Thakor (1993), who clearly spell out the functions of a commercial bank and guiding the institutions when lending to clients specifically on mitigation of credit risk. The other reason this work found it appropriate to use financial intermediation theory is because commercial banks under study are financial intermediaries, hence, their functions are fully guided by the proponents of this theory.

A financial institution is any individual player in a sector or industry that offers financial services, for example a commercial bank, the apex bank, and or an insurance company (Tobin & Brainard 1963; Tobias & Arturo 2010). Thakor (1996) defined financial intermediation from a brokerage service as a broker, thus intermediating financial transactions, importantly without need to change the transaction. Additionally, financial intermediation refers to the practice of ensuring financial capital is transformed into various financial assets, achieved by bringing lenders and borrowers together (Wray 2010).

Moreover, financial institutions can be classified as either banking institutions or depository institutions that comprise commercial banks, merchant banks, finance companies and or savings banks, while non-banking financial institutions include pension funds and insurance companies. Arguing on the importance of financial institutions, the following are their major functions: risk management, risk transformation, secured systems on both payments and settlements facilitated by banks, and extension of loans in the form of personal, commercial and mortgage loans, in addition to insurance products such as policies. Therefore, the entire industry of various institutions is known as a financial intermediary (Wray 2010; Tobias & Arturo 2010).

The existence of financial intermediaries is mainly attributed to some market participants or agents having excess funds, while others, especially entrepreneurs, experience deficits that need to be funded (Leland & Pyle 1977; Stiglitz & Weiss 1981; Diamond 1984; Boyd & Prescott 1986). In addition, borrowers and lenders never share common information, dictating the need for agents such as commercial banks, even with service at a cost; as they possess skills and tools such as loan models to separate bankable and non-bankable clients. Tobin and Brainard (1963) argued that financial intermediaries have capacity to appraise various projects, suggesting only quality and viable projects can be funded by a bank.

The second theory underpinning this study, a credit risk theory, is Credit rationing theory (Hodgman 1960), used to augment a Credit Score model. The Credit Score model was developed by Durand (1941), who then proposed that potential good clients could be distinguished from potential bad clients. He proposed a Credit Score model in which payment history, income level, employment history, and current obligations, as well as deposit paid, were assigned various weights; considered key elements in demonstrating a borrower's capacity to repay loan obligations. Borrowers with high Scores after credit assessment were then regarded as good, while borrowers with low Scores were regarded as bad.

Durand's (1941) Credit Score model can also be concurrently used with Credit rationing theory, which has an influence on loan evaluation at assessment stage. It was Hodgman (1960) who developed this theory that exhibits the firmness of banks

towards credit risk borrowers. The key elements of this theory are default risk, interest rate and demand curve, with scholars such as Miller (1962) and Edelberg (2003) having based their evaluations on this theory.

The third theory is Portfolio theory (Markowitz 1952), used to argue the Z-Score model as a credit risk theory. The Z-Score, introduced by Altman (1968), incorporates both traditional ratio analysis and statistical techniques, such as Multiple Discriminant Analysis (DA), to set a new level for bankruptcy prediction. Altman (1968) also developed a regression equation, with the Score being the dependent variable and ratios, namely retained earnings/ total assets, market value of equity/ book value of total debt, working capital/ total assets, and earnings before interest, as well as taxes /total assets and sales/ total assets as the independent variables. The ratios have different coefficients that signify contribution to the overall score and depending on the overall score, a borrower is then classified as being either good or bad.

Altman's model is closely linked with Markowitz's (1952) Portfolio Theory (Steinbach 2001). The principal argument of Portfolio theory is that the worthiness of investments, such as assets, should be evidenced by the significance of a portfolio's profitability. Portfolio theory can also guide a bank on how to invest in quality assets or assets with a low risk profile, as depicted by the Z-Score model. This theory uses risk, return and efficiency as the basis of analysis of creditworthy clients. Scholars such as Stiroh (2004) and Sanya and Wolfe (2011) have based their evaluations on this theory.

The fourth and final theory discussed is the Lender theory, which is a credit risk theory used to unpack the Asset-Based model developed by Orgler (1970). This author was motivated by evidence that showed NPLs were a result of inadequate attention paid to existing loans in the bank's portfolio. The study used a range of variables to obtain information from the financial statements in analysing liquidity, profitability, leverage, and activity ratios. Orgler (1970) used multivariate regression analysis to discriminate between good and bad loans and emphasised that Asset-Based model accuracy was centred on independent variables, strengthened by collateral.

Notable proponents of the Asset-Based model are Inderst and Mueller (2007), who developed the Lender-based theory. This theory proposes that in an imperfect market with intense competition, domestic banks have more information available in comparison to distance financiers or foreign banks. Commenting on this theory, scholars such as Brick and Palia (2007) and Arito, Koji and Lichiro (2008) stated that collateral becomes paramount in determining, evaluating, and setting limits of the requested loan.

The study has, however, for the enrichment of loan models in literature, also included several other alternative loan models, such as the, Olson O Score, Zmijewski Score model, Odam and Sarda's 1990 model and the 5Cs model.

3.2 Theoretical Framework

This section provides an in-depth discussion of the theories that guide this study, these being Financial Intermediation; Credit Rationing; Modern Portfolio; and Lender theory.

3.2.1 Financial Intermediation Theory

The theory under discussion was developed by Bhattacharya and Thakor (1993); with the basis of financial intermediation theory being the role financial intermediation plays in mainly focusing on business activities that extend the services of brokerage and qualitative asset transformation. These narrowed activities (Figure 3.1) are diagrammatically presented below:

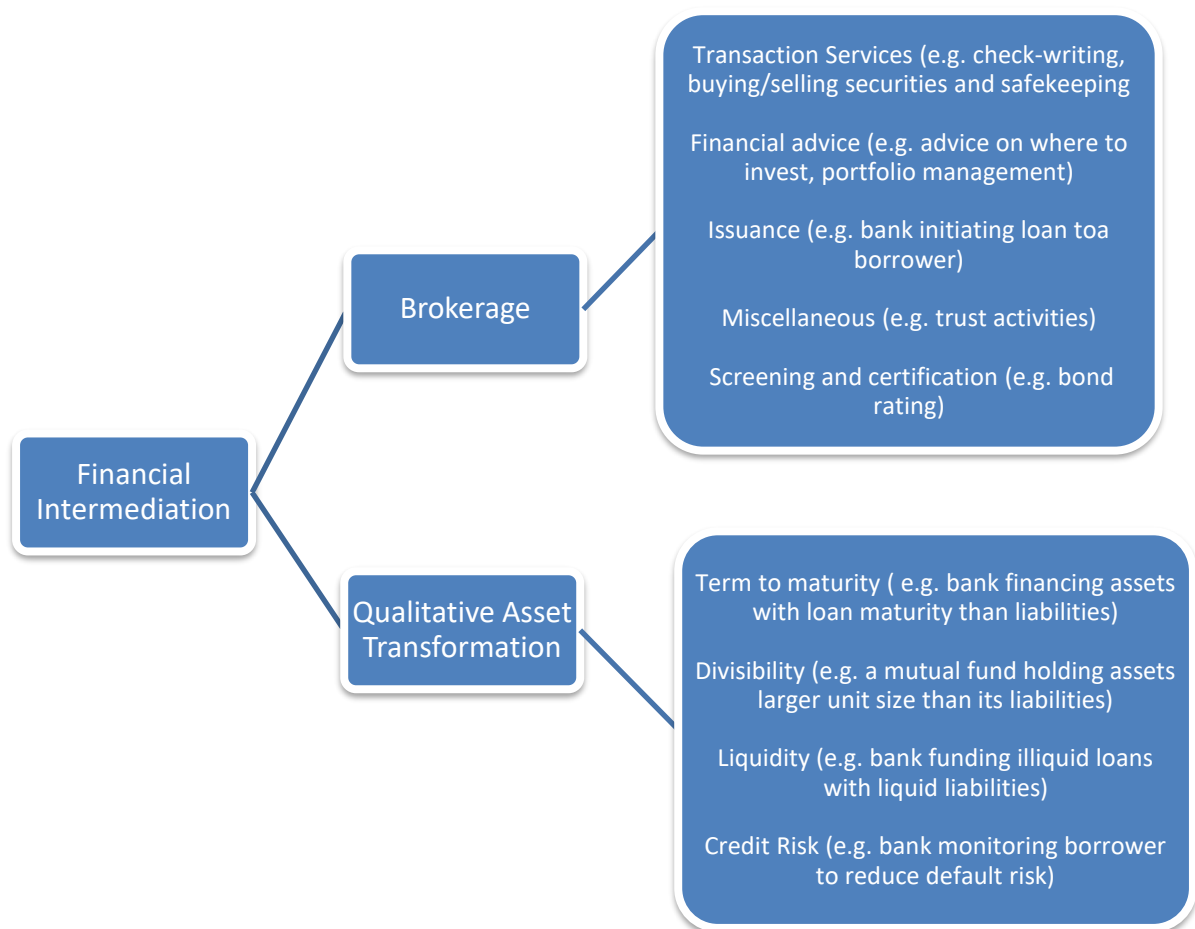


Figure 3.1: Brokerage and Qualitative Asset Transformation Diagram

Source: Bhattacharya and Thakor (1993)

Brokerage: refers to the process wherein financial intermediaries, such as commercial banks, bring together savers and borrowers without changing the nature of a transaction for a fee.

Transaction Services: commercial banks as financial intermediaries facilitate uncomplicated transactions, for example buying and selling of securities. Furthermore, other services can include the secure custody of client valuables in a safe.

Financial Advice: commercial banks as professionals and experts provide advice to their customers with regard to, for example, the range of products available on

investments, their returns and maturity period. In addition, advice can be given on how a client may diversify his portfolio to reduce concentration risk.

Issuance: commercial banks offer loan products to clients, therefore, the banks initialise the entire process and issue formal documents, such as a loan facility letter signed by both parties that can be used in a court of law in the event of disputes.

Miscellaneous (trust activities): commercial bank activities are diversified; they offer more than one service or product. For example, trust activities can be achieved by ensuring funds are always available for withdrawal when clients wish to access their cash or investment.

Screening and Certification: commercial banks perform comprehensive evaluation and analysis on all their services before they conclude any transaction to ensure no losses will be incurred, for example, on bond rating they will look at creditworthiness prior to considering it.

Qualitative Asset Transformation: refers to mediation and processing of anticipated risks or where risks inherited in a transaction are unpacked and mitigated.

Term of maturity: commercial banks ensure that in any transaction involving the bank and clients, precise terms are used, for instance, loan granted, from disbursement; the remaining life of the loan should be known by both parties.

Advisability rule: this refers to a situation wherein a commercial bank may facilitate investments on mutual funds, broken down as stocks, bonds, or other trading securities. Therefore, mutual funds are divided into several categories that accommodate any investor, determined by their capacity.

Liquidity: (funding of illiquid loans using liquid liabilities) this means banks attract deposits and investments to fund its loan book. Loan repayments also improve liquidity of a bank. Financial intermediaries such as commercial banks accept liquid deposits (short-term), on which long-term illiquid loans are granted; this process involves liquidity and maturity.

Credit risk: commercial banks consider the risk that a borrower will not meet its obligations leading to a financial loss, therefore, they focus on mitigating non-payment of loans from the outset and or at evaluation stage. This suggest that banks develop tools such as loan models, which help to identify potential defaulters. Furthermore, credit is only extended to creditworthy clients and this then needs to be monitored to ensure repayments are timeously received.

The theory of financial intermediary is of essence in this study because commercial banks that are deposit-takers, collect relevant information to facilitate banking transactions such as loan origination and, in the process, share various risks with borrowers (Allen & Gale 2004; Boda & Zimkova 2021). This study focuses on originating quality loans using loan models that mitigate defaults. Therefore, this work under financial intermediation theory is located under brokerage, which precisely dwells on issuance or origination of loans using appropriate tools to return quality assets. Further to this, the study is located under qualitative asset, specifically credit risk management. Commercial banks put all their effort into ensuring all money granted as loans shall be paid back by borrowers; this is achieved by using best tools to evaluate creditworthiness of clients, managing asymmetric information, risk management, and risk transformation (Bhattacharya & Thakor 1993; Scholtens & van Wensveen 2000, 2003). Following the granting of loans, all inherited risks are transformed, managed through risk transfer, thus shifting risk from one party to another. This can be achieved through the purchase of an insurance policy, actively managing risk that would have been absorbed, as well as close monitoring of clients (Allen & Santomero 1997, 2001; Scholtens & van Wensveen 2000, 2003; Boda & Zimkova 2021).

Financial intermediation theory is further analysed due to more than one theorist covering certain specific roles of financial intermediaries, either deposit taking or non-deposit taking institutions. The following are among financial intermediary activities, for example, reducing cost on information; delegation of tasks such as monitoring bank facility (loan) agreements; safekeeping of deposits; and transaction clearance; along with agency safety, are some of the examples of liability services (Diamond 1984; Diamond 2019; Leland & Pyle 1977). This is contrary to Bhattacharya and Thakor (1993), who maintained that financial intermediation theory should cover key

issues as follows: loan allocation, liquidity transformation, bank regulation, and maturity transformation, as well as borrower's own selection of resources. This was largely due to their role of providing qualitative asset transformation and brokerage services.

Even though scholars have hailed the above conception of financial intermediation guidelines, there are some scholars who found loopholes in the theory. For example, traditional intermediation theories were established on the foundation of transaction cost and asymmetric information, largely to explain institutions that are deposit-takers and insurance firms (Allen & Santomero 1997). Further arguments are that it did not accommodate new developments in the financial industry, which reveals that intermediation has remained pivotal.

Allen and Santomero (1997) argued that new markets being created for options traditionally between individuals and corporates, are now under purview of financial intermediaries. Therefore, the discussion on the role of financial intermediaries by making use of participation costs and risk trading, as opposed to the cost of long-established transactions and asymmetric information, is worth mentioning. In reinforcement of this argument, the rising asset shares of Mutual and Pension Funds are emphasised by Allen and Santomero (1997), in contrast with the falling share of assets banks and insurance companies held.

Meanwhile, Scholtens and van Wensveen (2003) concurred with Allen and Santomero (1997, 2001), in terms of the approach to apply when building a financial intermediation theory; this means functional (approach) as opposed to institutional. These authors, however, disagreed on the following aspects: risk management is not new but has always existed in financial intermediation; furthermore, their view on participation costs differed, as among the most outstanding factors for financial intermediation. This suggests that other elements, such as information asymmetry and risk management, were equally important. Additionally, existence of financial intermediaries was argued as not being a result of an imperfect market, but the fundamental reason is that of need for an agent when savers are transacting with borrowers; for example, the need for identification of savers as well as borrowers, remains the financial intermediary's key role.

Scholtens and van Wensveen (2000, 2003) shared the same sentiments as Allen and Santomero (1997) and these are echoed by Shy and Stenbacka (2017), to the effect that risk identification and mitigation are focal transactions. Similarly, risk management can be considered as a base of insurance, which initiates the transformation and management of risk by banks; demonstrated on exports by several merchant banks and insurance companies from Italy. Their arguments, which stem from loans and investments being associated with various risks, such as interest rate, liquidity and or credit risks, makes it important for a bank to mitigate all these risks, especially on new products and new markets availed in different geographical areas.

The model proposed by Scholtens and van Wensveen (2000, 2003) position risk and its management at the focal point of intermediation, with some risks dealt with that include, but are not limited to, maturity, market (interest and stock prices), counterparty, and life, as well as income expectancy risk. To act as counterparts, financial institutions make use of their reputation, balance sheet and off-balance sheet items, rather than their funds that are very limited. In reality, of all private enterprise forms, some of the most highly leveraged firms are financial institutions, allowing for their equity in obligations to their depositors. Tursoy and Faisal (2018) viewed deposits as economic enablers for growth in Cyprus, a sentiment shared by Unvan and Yakubu (2020). Whilst Brei, Borio and Gambacorta (2020) did not agree, they found that economic growth was not on the back of financial intermediation in Nigeria but other factors.

It is, however, important to note that, notwithstanding some critique of financial intermediation theory, financial intermediaries create value in the economy, as well as mitigating risks. In addition, this study's core focus is particularly credit risk management, which aims to reduce defaults and improve loan quality. Accordingly, banks have the capacity to mobilise resources and on-lend to their customer and where needed, they can also syndicate a transaction; this involves combining resources from other banks to raise a substantial amount for an economic value project. Financial intermediation theory is, therefore, applicable to this study due to the following reasons: Commercial Banks are agents of savers and borrowers; Commercial Banks assume risks in any transaction involving savers and borrowers,

with loans being of note. Some common risks faced by banks in executing their functions include interest rate, liquidity, credit, and operational risks, among others. The key risk in this study is that of mitigating credit risk, as it involves the probability of default by borrowers, which makes it imperative for a Commercial Bank to have a sound credit technique, such as loan models that enable a bank to distinguish potential bad clients from clients with prospects to pay.

3.3 Risk Management

Risk management underscores and explains the importance of banks as financial intermediaries, as argued by Scholtens and van Wensveen (2003), Bessis (2010), and Madeira (2018). Therefore, the key role of Commercial Banks as financial intermediaries involves the transformation and management of risk, with their contribution consequently adding to the economy of scale that impact societal welfare. Furthermore, banks encounter various risks in executing their business, with failure to mitigate the risks reducing profits and bank capital, made up of retained earnings, equity and subordinated debt.

Bessis (2010), as well as Khaled & Wahab (2019), identified the following risks (Table 3.1):

Table 3.1: Risks

Type of Risk	Description
Credit risk	risk of default by a borrower who fails to meet monthly obligations as per agreement
Liquidity risk	risk of failure by a borrower to meet obligations and or security provided cannot be sold quickly
Market risk	risk that a decrease is experienced, notably on trading or investment portfolios, due to market forces
Operational risk	risk arising from execution of a company's business functions.
Reputational risk	a type of risk related to the trustworthiness of business.
Macro-economic risk	risks that overlook an aggregate economy in which the bank operates, hence the need for a bank to have adequate capital that assists banks

	in managing their balance sheet, consequently, there is a need to risk weight the capital

Source: Bessis (2010), Khaled and Wahab (2019)

Default risk can, according to Bessis (2010) and Madeira (2018), be mitigated through hedging. This means holding some assets that exceed cash outflows or “match” outstanding liabilities. This makes a transparent system or structure imperative, as it can be accessed by customers for verification should they wish to be convinced or satisfied by the bank’s matching policy. Another form of mitigating default risk is by insuring, meaning the institution obtains guarantees as a contingency from its customers who have liabilities with them from AAA-credit-rated guarantors or government. Additionally, the bank raises top-up capital (capital cushion) beyond regulatory requirements, which can be used to collateralise such performance as future contracts and broker margin loans (Bessis 2010; Khaled & Wahab 2019).

This work involves qualitative asset transformation, especially credit risk; attributed to default or non-performance by a client who would have borrowed money from a bank (Muritala & Taiwo 2013; Kipsang 2014; Khaled & Wahab 2019). Therefore, it is important for a bank to assess all borrower applications prior to granting any loan to protect and preserve its capital. There are various methods of evaluating credit risks and traditionally, banks subjectively analysed their loans (Wang 2013; Altman 2018). Nonetheless, modern methods of evaluation comprise various models (Kennedy 2013; Shen, Nguyen & Ojiako 2013). As financial intermediaries who extend loans to borrowers, banks face credit risks, as Fabozzi *et al.* (2007) explained. Therefore, the study is guided by theories that minimize credit risk which are discussed below, such as credit rationing theory, modern portfolio theory and the lender theory.

3.3.1 Credit Rationing Theory

The Credit rationing theory is the brainchild of Hodgman (1960). The author put forth this theory as a guideline when loan applications are evaluated. It guides lenders on how to attain quality assets in the face of monetary policy changes, giving fundamentals of setting credit limits, called credit rationing, and resultantly reducing credit risk. It is thus about guidance on how to use Internal Credit Score results and

has been successfully used in microfinance application (Malhotra 2014); in household credit (Helsen & Chmelar 2014) and commercial lending (Ata *et al.* 2015). In the evaluation, the lender considers default risk, interest and the demand curve.

Default risk refers to a situation where there is a risk of borrowers failing to service their debt monthly or within an agreed period (Bessis 2010; Madeira 2018). The interest rate is the cost factor for a bank loan, used as a determinant to grant a loan (Castro & Santos 2010). The demand curve, according to Laing (2011), is a graphical representation showing the relationship between the price and goods or services demanded.

Meanwhile, diverse imperfections of credit market are utilised to demonstrate that it is rational for optimistic institutions to turn down credit requests, as opposed to adjusting interest rates upwards in the event of limited supply of loans (Freimer & Gordon 1965; Jaffee 1972; Jaffee & Modigliani 1969; Miller 1962). This argument suggests that inflating interest rates has some long-term effects such as NPLs. There has also been some critique of this theory. Credit rationing is a result of a rise on default risk, mainly attributed to an increase on extended debt, as well as interest (Jaffee & Modigliani 1969). They further asserted that the other reason for credit rationing was due to risk-inclined clients in certain groups, as classified by the bank. Furthermore, any borrower whose demand was above average poses a risk to default to the bank (Possner, Burns and Musshoff 2021). Stiglitz and Weiss (1981), Jaffee and Stiglitz (1990) and Beck *et al.* (2018) maintained that interest rates do not always compensate fully for credit risk, suggesting that a highly priced loan is expensive, making it difficult for borrowers to service debt when it reaches a certain level, consequently creating bad debts.

Leland and Pyle (1977) asserted that a good proportion of investor equity exhibits fruition of investment, hence the probability of servicing its obligations is high. In another view, Stiglitz and Weiss (1981) observed that security reduces risk when requirements for security and applicable interest rates are set together, therefore, there may not be a need to ration credit. Nevertheless, security does not fully mitigate default risk; largely due to its nature such as the liquidation process, which will increase transaction costs (Jaffee & Stiglitz 1990).

In a different dimension, arguments were made to the effect that not only was there credit rationing by banks but complete declines were experienced and of concern was that it was only appending to certain races (Munnell *et al.* 1996; Cavalluzzo & Cavalluzzo 1998; Cavalluzzo & Wolken 2005). In their view, it is imperative for appropriate pricing to be put in place in line with risk grade, which should be applied to any borrower, suggesting that merit of an application is based on credibility. However, the theory does not give assurance of loans performing. The study was not clear on usefulness of the theory and loan performance. However, Kisaka (2016) and Antoine, Stanislas, and Gustave (2021) found that credit rationing indeed does improve loan book quality.

In a completely different version of rationing, some arguments from Calomiris and Mason (2003) and Calomiris and Wilson (2004) revealed that deterioration of a bank leads to deposit withdrawals by customers, contrary to interest demand. Therefore, deposit rationing is not only related to liquidity challenges but also to limited incentives, as well as market information. The Credit Rationing Theory was introduced because it explains key factors considered for a loan limit following a credit Score obtained at evaluation stage (Becket *al.* 2018).

3.3.2 Modern Portfolio Theory

Developed by Harry Markowitz in 1952, modern portfolio theory stated that it would be more practical for an investor to maximise the anticipated return while minimising the variability or risk of returns. This should be done by engaging or investing in a diversified or varied portfolio of assets, with different price movements peculiar to a given market (Rice 2017). Using the Z-Score outcome, the lender can consider granting loans to clients with efficient portfolios in various sectors, consequently reducing credit risk.

An efficient portfolio refers to a situation wherein a comparison to other investment shows that notwithstanding variances and risk, the results in the portfolio enjoys higher yields (Bessis 2010). A combination of both high and low risks and moderate returns is expected to yield decent returns. Using the Z-Score model outcome, the bank has a choice of combining assets with varying levels of risks and returns. There is a probability of loan performance but no guarantee.

Risk, as Aven (2011) explained, is an unexpected deviation of attained result from those anticipated. The variance of anticipated results is also likely to differ from the real results. Therefore, to avoid a high probability of NPLs, credit risks precautions and measures should be exercised by the lender. Furthermore, returns are an additional income from the initial investment, which may come in the form of dividends or interest, when the banks' assets perform due to success in credit risk management and when initial investments appreciate.

Critiques of the theory were as follows: Modern portfolio theory has been rejected by some scholars when they argued that focusing future assets by analysing mean and variance were not appropriate parameters for decision-making by lenders (Sharpe 1967). Frankfurter, Phillips and Seagle (1971), along with Omisore, Yusuf and Nwifo (2012) also averred that estimation error remained high, hence were not convinced on the effectiveness of mean-variance as an approach applied on portfolio selection. The theory does not, at any given time, provide guidance in forecasting credit risks that can be computed to determine risky assets through arguments anchored by Bodie, Kane, and Marcus (2009), as well as Kazan and Uludag (2014).

Furthermore, modern portfolio theory was still lagging in terms of full implementation, largely due to the difficulty in estimating the form of information input that would give accurate estimates on most asset performance (Elton, Gruber & Padberg 1976). Additionally, it is costly and took a prolonged time to complete computation of efficient portfolios; complemented by unavailability of managers to oversee portfolios and view risk return of portfolios. This became critical in utilisation of the theory, thus reducing effectiveness probabilities.

Concerns on risk measurement were voiced since establishment of the theory, yet it remains in use (Steinbac 2001; Njeru, Dominic & Fredrick 2015). Appropriate risk is derived from normal distribution (Sanford 2005), while Sciubba (2006) also argued on the theory's efficiency, it is questionable as it fails to accurately predict asset performance evidencing weak credit assessment. The following arguments are raised concerning the theory: it places reliance on assumptions, risk/ return linear is positive, risk/ return has a static relationship, and some parameters are correctly estimated, for example, expected return and client make-up in the market (Lo 2012).

The study selected modern portfolio theory with regard to loan assessment using the Z-Score model. This theory was selected because it provides guidance regarding the best way of selecting investments, guiding a bank where there is high credit risk especially in unstable economy such as for Zimbabwe.

3.3.3 Lender-based theory

Inderst and Mueller developed and adopted a Lender-based theory of collateral in 2007. The theory relates to the credit market, with a particular emphasis on collateral; giving weight to the use of collateral security in the credit market, ultimately reducing credit risk. The main assumption of the theory is that an imperfect market, with intense competition within domestic banks, has more information available when compared to distance financiers or foreign banks. The role of collateral is, therefore, to minimise credit decision distortions that are centred in soft, private information. This corresponds with the Asset-Based model that emphasises the awarding of credit in line with collateral pledged that reduces credit risk.

Local lenders increase collateral requirements, guided by model Scores that determine credit risk, as well as credit limits. The information revolution in business competition from transaction lenders infers loan rate reduction by local lenders raises requirements for collateral. Inefficiencies can be mitigated by collateral and local lender incentives to accept marginal projects improved, resulting in more efficient credit decisions (Inderst & Mueller 2007).

The theory has been tested and criticised on the use of collateral for business loans as credit risk mediatory measure (Jimenez, Salas & Saurarina 2009; Caballero, Farhi & Gourinchas 2017) Contrary to this, security is regarded as in line with the lender-based theory and used as an evaluation technique by lenders to distinguish potential bad and good accounts, thus mitigating credit risk (Chan & Kanatas 1985; De Jonghe *et al.* 2020). While arguments from Besanko and Thakor (1987) revealed that a lender-based theory shows opposite opinions on borrower performance predictions and that of the bank, thus weak credit risk measures. Accordingly, there is a need to test the theory in an unstable environment such as Zimbabwe.

While Jimenez *et al.* (2009) explained that information on predictability of theory is not sufficient, there are other arguments that support the theory, clarifying the need of ex-ante and ex-post clarifications on the requirement for security. In lender-based theory, use of available information was also argued by Agarwal and Hauswald (2010) to be too reliant on lender and borrower proximity. This is echoed by Bellucci, Borisov and Zazzaro (2013), who agreed the theory was too dependent on proximity to obtain information for lending decisions and managing credit risk. Moreover, there are fewer security requirements, suggesting the bank takes comfort in clients visiting any time because it is accessible. In addition, the bank can view client operations at any time because they are located close to each other, unlike long-distance clients whose business is not visible all the time. Nonetheless, proximity to client is not a source of payment by borrowers but assists the bank in monitoring credit risk events.

Further concerns on the lender-based theory showed arguments skewed towards missing variables that could assist in what exactly influences the need for security, following ex ante characteristics of clients who would have borrowed (Bharath *et al.* 2011). Additionally, rates applied suggest use of soft information provided by borrowers. On the other hand, arguments on security monitoring and enforcements also erupted, there is need to monitor clients which fails to pledge security or adequate security (Ono & Uesugi 2009). Nevertheless, value of security also determines monitoring sequences complemented by enforceability of the pledged security (Cerqueiro, Ongena, and Roszbach 2016; Ivashina, Laeven & Moral-Benito 2020). Lender-based theory explains and endorses security as fall-back position or source of repayment. The above review of Lender-based theory has shown security, in one form or another, as the pinnacle of this theory in the function of a credit risk mitigatory measure.

3.4 Lending Technologies

Banks are motivated to lend due to interest income earned per transaction (Altman and Saunders 1998). Lending is the practice of extending loans to clients, with a signed contract in place that states the borrower will pay back the money later date (Lipscombe & Pond 2002; Ferri *et al.* 2019), It is therefore important for any lending institution to identify their best clients who are creditworthy in order to mitigate risk of

default. Furthermore, this is achieved with modern tools such as loan models, which are under study.

Berger and Udell (2006), advise that there are basically two main lending technologies, namely lending that is either transaction- or relationship-based (Cornée 2019). The technique that uses readily available information regarding clients to feed into the banks' loan performance prediction models is known as transaction-based lending (Aiyar 2012). Although relationship lending is predominantly based on the personal relationship of lender and client, as well as information gathered during discussion, six approaches are applied to transaction-based lending technologies:

- (i) Financial statement lending,
- (ii) Small business credit scoring,
- (iii) Asset-based lending,
- (iv) Factoring,
- (v) Fixed-asset lending, and
- (vi) Leasing.

The two technologies respectively use different types of information that is hard quantitative information, which is basically financial information from financial statements (transaction based). Berger and Udell (2006) argued that hard information can only be in quantitative form. Soft information is basically information obtained qualitatively, either through interviews or discussion or any form that is personal (Berger & Udell 2006; Cucculelli, Peruzzi & Zazzaro 2019), Cole (1998) asserted that a bank is not likely to extend a loan to a client with whom it has had a relationship period for less than a year.

In Zimbabwe, Commercial banks apply various lending technologies as illustrated (Table 3.2); this shows transaction-based lending as the most dominating technology applied by financial institutions.

Table 3.2: Lending Technologies in Zimbabwe

Class of Lending Technology		Participating Institution	Lending Technology		
Transaction Based			1980	2000	2018
Annual Financial Statements		Commercial Banks, Merchant Banks, Finance Houses	Active	Active	Only Commercial Banks were active
Small Business Credit Scoring		Commercial Banks, Merchant Banks, Finance Houses	Active	Active	Only Commercial Banks were active
Asset Based Lending/Leasing/Equipment & Motor Vehicle		Leasing Companies, Finance Houses, Merchant Banks	Active	Active	Only Commercial Banks were active
Fixed Asset Based Lending	Commercial and Residential Real Estate	Building Societies	Active	Limited Activity	Active
	Commercial and Residential Real Estate	Commercial Banks	Not Active	Not Active	Active
Relationship Lending					
Relationship Lending		Commercial Banks	Active	Active	Active

Source: Developed from Berger and Udell (2006) and Nyangara (2013)

Table 3.2 shows different types of lending technology that suit particular categories of financial institutions. It is not always the case to find one lending technology that can be applied across all institutions because of different products offered.

The commercial banks, notwithstanding the use of various lending technologies, are also supported by various loan models to analyse creditworthiness of a borrowing corporate client, discussed hereafter;

3.5 Loan Models

The models under discussion, such as Internal Credit Score, Z-Score, Asset-Based and others, were critically analysed in order to identify any existing knowledge gap this study aims to address. Furthermore, loan model literature was also used as a reference point for the study results discussed in Chapter 6. Arguing on the importance of literature, Boote and Beile (2005) reiterated that a well-developed literature review provides the basis of a good research project, whereas a flawed literature review usually results in poor research.

3.5.1 Development of Credit Score Model

It has been more than six decades in which the development of Credit Score has been within the academic space. Durand (1941) was the first scholar to undertake a study on internal credit scoring, after recognising that using various techniques could be useful in distinguishing best clients from potential bad clients. In developing the model, the study presented a statistical approach to the analysis of certain pertinent risk elements of borrowers. Some factors were classified as financial, with non-financial factors considered significant in credit extension also analysed. Down payment, length of contract, security of loan, and borrower assets as well as liabilities were taken as financial factors, while the non-financial factors were stability of employment, stability of residence, personal characteristics, and purpose of loan.

In his study, Durand made suggestions calling for systems that could be used in discriminating potential quality loans and for identifying expected NPLs. Information used in that study was obtained from a target population made up of “Commercial Banks operating personal loan departments, personal finance companies, industrial banking companies, automobile finance companies and appliance finance companies”. Notably, the client’s personal information with regard to performing loans and NPLs were obtained from their application forms, with various demographic variables employed, such as age, marital status, number of dependents, stability of residence, occupation, and assets and liabilities. A questionnaire was used to collect the data.

Various techniques have been used to develop an Internal Credit Score model. They are predominantly quantitative techniques, categorised as parametric and non-parametric. A parametric is any quantitative technique associated with permanent parameters that establish or define a probability model, for example, discriminant, probit and regression analyses (Anderson 2007). Similarly, methods are determined by known factors of the population under investigation, notably a normal population. The typical distribution can also be used to approximate factors of population, while common parameters are the mean and standard deviation that require ratio or interval data such as income, age or weight.

A non-parametric technique is any quantitative method that works with limited assumptions about underlying data. It does not depend on population of interest because neither the set of parameters nor distribution used are fixed. Examples of non-parametric techniques are algorithm, Chi-square, neural networks and genetic programming (Anderson 2007). This suggests applying this method mitigates constraints such as assumptions concerning the population, facilitating use of the techniques. Nominal or ordinal data are generally employed, with qualitative techniques such as judgemental analysis used (Abdou & Pointon 2011). This type of analysis relies on lending team' knowledge, using both past and currently obtainable experience, in assessing a borrowers' capacity to service the loan obligations complimented by their character (Abdou & Pointon 2011). The method is related to subjectivity, unpredictability, and distinct preferences for motivating decisions.

Additionally, Durand employed a parametric statistical technique to analyse the data, namely DA. The general programmed DA formula is as follows:

$$Z = I + {}_1X_1 + {}_2X_2 + nX_n,$$

Where:

Z represents the discriminant (zed) Score,

I is the intercept term, and

i represents the respective coefficient in the linear combination of explanatory variables,

X_i , for $i = 1$ to n

(Lee *et al.* 2002).

DA is a technique used to shorten the gap among a group of cases and expand the divergences among different group cases (Anderson 2007). According to Marcoulides and Hershberger (2014), DA has a set of predictions based on independent variables used to classify individuals into groups (good or bad group). The main aim of the technique is to classify clients according to their financial status, achieved by predicting future loan performance through a predictive equation for classifying new applicants. The programmed equation, therefore, shows

relationships among variables. In addition, high or low values come from different groups and can thus be applied to the data, which may discriminate amongst groups.

The main advantage of DA is that the technique can forecast group membership whenever more than two known groups exist (Anderson 2007), while the main challenge is that it is affected by all assumptions linked to the employed statistical technique. When predicting rare groups, this leads to high misclassification errors. Furthermore, the technique utilises linear functions prediction, as opposed to quadratic functions, causing errors when separating non-bankable projects (Abdou & Pointon 2011). The results are, however, affected by some or all assumptions associated with the statistical technique, while normally distributed error terms are also common.

Importantly, Durand's main findings were that performing loans are a result of various conditions or factors such as stable employment and the socio-economic level of borrowers; professionals; permanent residence at one address; large deposit payment that reduce credit risk and monthly commitments. The study also found older people and women generally respected their credit terms compared to men. It also found out that NPLs were caused by unstable employment of borrowers; young borrowers who were not committed to their obligations; and borrowers with no fixed address who could default and disappear. It was further noted that credit risk was not threatened by several dependents of a borrower. The noted gaps suggest it may not be appropriate to rely fully on this model, hence the need to undertake this study.

3.5.2 Enhancement of Durand's Credit Score Model in Developed Countries: Period - 2000-2011

Durand's (1941) credit score concept became a subject of scholarly enquiry, with scholars across the globe either supporting, adding or refuting his method and findings. Interestingly, a general overview on the Credit Score model by Thomas (2000) in the USA added a very important aspect to the Credit Score model; the behavioural aspect. The study argued that behavioural scoring involves analysis of existing clients' facility, where the institution uses existing Credit Score model variables and then adds repayment trend on current loan of client. Furthermore, this model proposed a cut off period of observation of at least a year.

The model could also be built on the back of operational research results. In that analysis, Thomas retained DA as the analytical tool, with the economic condition added as a new critical variable to build a robust Credit Score model, thereby suggesting the need to incorporate inflation rates, interest rates and GDP. In addition, Thomas' study concluded that the use of gender and religion in determining client capacity to repay borrowed funds is illegal, arguing its elimination on the list of variables. However, this is contrary to Durand, who found gender to be an important risk factor because women had proved to be better performers compared to men. Furthermore, profitability of the client as well as recovery prospects can only be achieved when a loan model is utilised throughout the loan's life span. Consistent use of a loan model is, therefore, imperative to attain a quality loan book.

Frame, Padhi and Woosley (2001) conducted a comparative study in the Southeast USA between Low- and Moderate-Income Areas to establish the effect of large banking organizations using the Credit Score model on small business lending. These scholars made their arguments on the existing Credit Score model utilised by large banking organisations in the area. Specifically, four different types of data were used to support the arguments, namely; for each census tract, demographic data and business information; bank data at census tract as well as Institutional levels, and survey data regarding Credit Score model use by large banking organizations, which were all examined. Furthermore, data were consolidated to establish small business lending activity determinants by large banking organizations using Regression analysis, a technique that analyses the correlation between a categorical dependent variable and a set of independent variables (Osborne 2015).

LR is used when the dependent variable has only two values such as "0 and 1" or "yes or no". It depicts ratios, likelihood, confidence limits and deviance of items. Therefore, it can be used to ascertain intervals on predicted values and help demonstrate optimum credit Score cut-off points for classification. The general formula of a regression technique, wherein the probability of a dichotomous result (zero or one) is skewed to a set of potential forecaster variables, is:

$$\text{Log} [p / (1-p)] = I + {}_1X_1 + {}_2X_2 + nX_n,$$

Where p computes the probability of the outcome of interest; β_0 is the intercept term, and β_i characterises the respective coefficient incorporated in the linear combination of the variables; X_i , for $i = 1$ to n .

The dependent variable is represented by the logarithm of the odds, $\{\text{Log}[p/(1-p)]\}$, and a ratio of two probabilities of the expected outcome of interest is obtained (Lee *et al.* 2002).

Hand and Henley (1997) maintained regression analysis has, in the world of Credit Scoring, proved to be superior on classification results. Anderson (2007) concurred and argued the main benefit of applying this technique is the outcome of LR that falls within the 0 to 1 probability, which is actual or close to actual prediction, thereby making it effective. While it is effective, its major weakness is too many computations that cannot be understood by a layperson.

The Credit Score model thus increases the lending chances 2.5 times more for Low- and Medium-Income business as that projected for higher income census tracts. Similarly, Credit Score use raises the possibility that a large banking organization will, in a census tract, provide loans. Generally, these results propose there is benefit to low-income areas from technological enhancements (Credit Score model); at times, these benefits exceed those that higher income areas experience. In addition, it can also be deduced from the study that the Credit Score model does not discriminate against applicants, regardless of their income levels and geographical location. The model also mitigates bias and requires all relevant information to enable applicant evaluation.

A further quantitative analysis of the Credit Score model was undertaken in Turkey by Emel *et al.* (2003), whose arguments were strengthened by introducing the Data Envelopment Analysis, allowing a multi-dimensional financial ratio analysis to be embedded in the Credit Score model algorithm. The analytical methods used were regression, discriminant and expert judgement analysis, from data or existing company knowledge. A total of 46 ratios not used before were employed and categorised into groups in line with their characters with similar mathematical

features. Ratios were determined by factor analysis; a process that saw four of the ratios discarded, with the remaining 11 factors and ratios used, as outlined below:

Factor 1 - Bank loans: These include short-term bank loans/net sales; total bank loans/net sales; Short-term bank loans/current liabilities; and Short- and long-term bank loans/total assets; in addition to financial expenses/net sales; domestic sales/net sales; Exports/net sales; and Total bank loans/total liabilities.

Factor 2 - Fixed assets: These incorporate net materials, fixed assets/owners' equity, fixed assets/long-term liabilities and owners' equity.

Factor 3 - Profitability: This consists of profit before tax/total assets, profit before tax/owners' equity, profit before tax/net sales, and operating profit/net sales, as well as net profit after tax/owners' equity and net profit after tax/total assets.

Factor 4 – Leverage: This is made up of current liabilities/owners' equity, short- and long-term liabilities/owners' equity, depreciation ratio; current assets/total assets, current liabilities/total assets and owners' equity/total assets.

Factor 5 – Miscellaneous: This involves current liabilities/net sales, average collection period of trade receivables (days), average payment period of trade payables (days), and short-term bank and creditor loans/net sales, along with Asset turnover.

Factor 6 - Liability term structure: This includes Current liabilities-CIA_b /total liabilities-CIA; Current liabilities/total liabilities.

Factor 7 - Liquidity: This incorporates Liquidity ratio and cash ratio.

Factor 8 - Sales and Costs: These are made up of gross sales/net sales and cost of goods sold/net sales.

Factor 9 - Miscellaneous: This incorporates current ratio and other liabilities/total assets.

Factor 10 – Miscellaneous: This is made up of net working capital turnover rate and current liabilities (owners' equity and long-term liabilities).

Factor 11 – Miscellaneous: This incorporates extraordinary income/net sales and other receivables/total assets.

Ratios discarded in the factor analysis included:

- inventory turnover period,
- net working capital ratio,
- extraordinary expenses / net sales,
- gross profit margin,
- material fixed assets accumulated depreciation / total assets accumulated depreciation,
- construction income accruals,
- trade receivables collection period and
- inventory turnover period trade payables payment period,
- net working capital / (current liabilities less payables to shareholders, participations, affiliated companies and construction income accruals).

Emel *et al.* (2003) argued that along with Data Envelopment Analysis' overall explanatory power, all the financial ratios used, except for one, were able to significantly explain Scores, showing a measure of financial efficiency that is multi-dimensional. The validation of the effectiveness of the Data Envelopment Analysis was made against regression and discriminant analyses results, which were successful.

Batista (2009) undertook a study in Portugal on the development of a Credit and Behavioural Score model for credit cards and maintained that the key feature of the Behavioural Scoring model is based on evaluation of existing clients, who already enjoy banking facilities or to whom a loan has been extended. The main aim was to assess their performance to date and how they may perform before expiry of their facilities. This is contrary to the Credit Score model, which evaluates a completely new applicant who does not have a relationship with the bank. Characteristics such

as the number of divorced, unresponsive, separated, single and widowed clients were observed. Additionally, Batista's (2009) study captured new additional variables, such as:

- scoring for current customer account,
- credit limit,
- current account identity,
- account classification,
- amount revolving (not paid in last statement),
- renderability (monthly return value account),
- month to which data refer,
- description of state code,
- delinquent account for more than 60 days,
- date of birth,
- educational qualification,
- geographic region and
- profession.

Notably, the study established key factors identified by the statistical technique as: scoring, credit limit, current balance, and renderability, as well as age, account class, revolving balance and description of state. Therefore, model validation was conducted through an out-of-sample of both good and bad clients and applied to the LR model, according to the following equation:

$$(Y_i=1) = 11 + e^{-Z_i + \varepsilon_i}$$

$$\text{On that } Z_i = \beta_0 + \beta_1 x_{1i} + \dots + \beta_k x_{ki}$$

Where:

β_k represents the model parameters;

x_{ki} the variables that represent the factors explaining the probability of each user being a good payer.

$$Z_i = -49,89290 + 0,066500 \times A + 0,000261 \times B + 0,000499 \times C - 0,008396 \times D + 0,0186 \times E - 0,602927 \times F - 1,434070 \times G - 0,000384 \times H - 0,578892 \times I - 0,808648 \times J$$

$$p(Y_i=1) = 11 + e^{-(-49,89290 + 0,066500 \times A + 0,000261 \times B + 0,000499 \times C - 0,008396 \times D + 0,0186 \times E - 0,602927 \times F - 1,434070 \times G - 0,000384 \times H - 0,578892 \times I - 0,808648 \times J) + \varepsilon_i}$$

94%

A major finding of the study is that Behavioural scoring facilitates prediction of near future performance. Meanwhile, developing a successful model database should be done properly, even though such a process is associated with high costs. Essentially, this scoring methodology can also be applied in other areas such as insurance, business intelligence agencies, marketing, as well as in production management and human resources.

3.5.3 Enhancement of Durand's Credit Score Model in Developed Countries: Period - 2011-2017

In the United Kingdom (UK), a study by Abdou and Pointon's (2011) did not develop a new Credit Score model, with arguments based on a consolidation of 214 articles, journals, theses and books, and selected major findings. This was contrary to their previous study that took place in Egypt in 2007, wherein they developed a new Credit Score model for a Commercial Bank. In the study, arguments were made on different statistical techniques being used, for example, regression and probit analysis, along with neural networks, and expert systems, in addition to linear regression, genetic programming, decision trees, and judgemental technique.

Paliwal and Kumar (2009) developed what they called the Expert System; described as collaborative, computer-based, with the application of facts and heuristics to resolve complex problems and regarded as uppermost level in terms of intelligence and expertise of a human being. The system is significant in generating computer-based applications and ensuring their usefulness in financial decisions, while enhancing the system of separating good and bad accounts. The Expert System became very useful when incorporated into various models used for fraud in credit cards, prediction of bankruptcy and bank failure, pricing of options, and application for mortgage, as well as the possibility of systems being automated. A major criticism of the system is its mathematical makeup or construction, which makes it difficult to understand, while other drawbacks include its subjectivity, inconsistency and individual expert's preferences that may not be compatible, along with the excessive amount of time required to find the optimal configuration of neural networks, which may delay lending decisions.

Neutral networks, developed by Medsker (2012), comprise mathematical computer techniques prompted by a human expert brain's influence and is highly instrumental in problem-solving methods. Using linear or non-linear variables, the system helps to distinguish good and bad accounts. Neutral networks could determine all interactions on predictor variables. Nonetheless, the extensive computational task and development of a model that is empirical in nature, make it a non-favourable technique.

Decision Trees were also observed as a statistical technique applied when building a Credit Score model. According to Breiman (2004), this is a non-parametric method employed to analyse variables that are either dependent and or categorical, as a function of continuous explanatory variables. Where a classification tree is used, a dichotomous tree is built when the records are split at each node, based on a single input function. To find the best one, the system considers all possible splits, selecting the winning sub-tree according to either its overall rate of error or lowest misclassification cost.

Paliwal and Kumar (2009) evaluated and argued the simplicity of understanding, interpreting and having value through Decision Trees, even with minimal hard data. It is possible to generate important insights based on a situation (its alternatives, probabilities, and costs) described by experts and their preferences for outcomes. This technique contributes towards determination of the values that are worst, best and expected for different scenarios and can also be combined with other decision techniques. The authors highlighted some setbacks associated with Decision trees, such as instability, which implies a small alteration to the data can result in a large change in the optimal Decision Tree structure.

Abdou and Pointon (2011) also observed the different manner in which each bank selects effective variables, normally according to the nature of the data and economic or cultural fundamentals that could affect the model quality and its suitability for a specific market. Furthermore, these variables have no optimal cut-off Score point and differ from one country to another. The key findings include customer service improvement and retention of creditworthy customers due to quick turnaround times, facilitated by the model. Additionally, variables employed are correlated with

repayment performance; both statistically and significantly. The same data provided by a borrower can be evaluated by any bank lending officer due to consistency of the model.

In Pakistan, Samreen and Zaidi (2012) developed a Credit Score model focusing on individual clients of a Commercial Bank. The study utilised techniques such as LR and DA. Moreover, dual income was added in as a new factor to be considered in a Credit Score model. The study argued that although a Type ii error has more impact than a Type i error, it does not cause any trouble because a good applicant remains good, even in the credit analysis. Hence, the model is the most effective, accurate, efficient and useful. The key finding from the study by Samreen and Zaidi (2012) was that marital status was a strong predictor of credit risk, contrary to previous results.

Samreen, Zaidi and Sarwar (2013) developed a Credit Score model focused on corporate clients of a Commercial Bank. The study utilised regression analysis and DA for classification of clients which were all accurate. Their argument on the effectiveness of the model was based on new variables added, which were: current ratio; quick ratio; gross profit margin; operating income margin; net profit margin; return on assets (ROA); return on equity; sales growth; debt to equity; total debt/assets; interest coverage ratio; debt service coverage ratio; debt leverage; receivable turnover days; sales in inventory; payable turnover days; earnings per share; and credit rating.

An accuracy rate of 100 percent or correct classification was used to validate effectiveness of the model developed by Samreen *et al.* (2013). The main finding here was that in mitigating Type i and Type ii errors the Credit Score model was strengthened.

Hurley and Adebayo (2017) undertook an overview and argument of the Credit Score model using Big Data; which is a credit evaluation method based on the information obtained from individual behaviour found on any data points extracted from borrower activities, both online and offline. These sources of data include information, obtained by electronic means, of records such as consumers' browsing tendencies, social

media activities and geolocation data. This means borrowers are evaluated based on behavioural analysis, as opposed to creditworthiness.

Challenges in using big data are attributed to insufficient transparency as well as the high probability of inaccurate input data by Hurley and Adebayo (2017), who added that tools may target a certain category, such as vulnerable consumers, while bias cannot be ruled out due to lack of transparency. The method does not seek consumers' consent either. Consequently, consumers cannot verify the information and thus, may be unfairly misclassified. Furthermore, borrowers may become creditworthy merely because of their association with certain groups, while in a different situation, some vulnerable groups can be trapped in debt. This kind of approach is largely applicable in modern societies and developed nations such as the USA and not validated.

Markov, Seleznyova and Lapshin (2022), on the one hand, determined that utilising public datasets validates effectiveness of a credit score model. On the other hand, Zhang *et al.* (2019) confirm that the credit score model can successfully classify clients and bank can make adjustments such as adjusting thresholds. Logistic regression is a regarded technique in developing a credit score due to its conformity with Basel II standard (Goh & Lee 2019). Markov *et al.* (2022) illustrate that utilising public datasets validates effectiveness of a credit score model.

3.5.4 Enhancement of Durand's Credit Score Model in Developing Countries: Period - 2011 – 2017

In Africa, scholars have undertaken research on the Credit Score in countries like Egypt, Kenya, Tunisia, and Zimbabwe. In Egypt Abdou, El-Masry and Pointon (2007) argued that certain variables employed in a credit scoring system may result in social discrimination, for example, sex, age, marital status, income and level of educational qualifications, even while the variable may appear neutral to the statistician. The study applied DA, LR and probit analysis as techniques. Probit analysis for instance is an analytical tool which uses cumulative and quantile functions and is widely employed when evaluating acute toxicity data principles in performing credit analysis. Hence, it shows the probability of servicing a loan based on available data (Hayes 2008). The general formula of probit analysis is:

$$Prob(y = 1) = \Psi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)$$

Where y is the zero-one binary outcome for a given set of value.

Ψ is the value from the cumulative normal distribution function.

β_0 is the intercept term, and

β_i represents the respective coefficient in the linear combination of explanatory variables, X_i , for $i = 1$ to n .

The variables used in the study were the loan amount and its duration, the company or a branch, additional income, and whether the house is owned or rented, in addition to house rent, loan tenure, home telephone, and utility account, title/position, as well as education level, relation with other banks, status of credit card, and corporate guarantee, along with other guarantors. Use of the average classification from the three techniques applied, as well as misclassification cost, were used to validate the effectiveness of the new Credit Score model. Misclassification cost is calculated as $P(\text{bad/good})$ and $P(\text{good/bad})$, and it measures the likelihood of Type i and Type ii errors. The findings reveal the new model was more effective, with a classification rate of 75 percent, compared to other systems in use. This was an important contribution to the discourse.

Using LR as a statistical analysis technique, Oriema (2012) utilised a behavioural credit scoring model on cardholders for a study in Kenya. Potential debt was argued with factors such as overdrawn account, times overdrawn, number of missed payments and value, as well as number of cash withdrawals, while a 2-year history makes that observation tangible; though it could be reduced to a period of 12 months. Therefore, the population that may be evaluated with a new Scorecard, could be different from the population originally built on. The most influential variables that determine default probability were identified as past due days, average amount due in the past six months and utilisation.

Mpofu and Mukosera (2014) surveyed Credit Scoring techniques in Zimbabwe. They used factors such as financial indicators, for example, gross income of household, demographic indicators, for instance dependant numbers, home status, address district; and employment indicators including employment type, number of years

previously employed, checking account for behavioural indicators, and average current account balance, as well as defaulted or delinquent loans, number of annual payments and collateral. This study confirmed the existing statistical techniques for developing a Credit Score model as: linear regression, DA, probit analysis, decision trees, LR, artificial neural networks, and fuzzy algorithms when building credit scoring models.

A Fuzzy algorithm is a computer-based scoring technique that applies a mathematical theory of fuzzy sets, which reveal inaccuracies and uncertainties such as account classification (Verbruggen, Zimmermann & Babuska 2013). The technique can easily separate data as either true or false, making it a flexible technique and essential for the involvement of experts when building it. Furthermore, it eliminates most Type i errors. This technique can also manage inexact information, such that the solution offered is of high quality. Anderson (2007) argued the technique is further able to provide solutions in an environment that is not static. Additionally, several intelligent agents may be applied to evaluate customers over several criteria and fuzzy judgement, thus making a sound output (Yu, Wang & Lai 2009). There are, however, concerns with regard to computational and turnaround time posed by the Fuzzy algorithms technique, for instance, delayed decisions made by the systems (Anderson 2007). Similarly, it also tolerates inaccuracies, though they may be used to reduce challenges not resolved before.

Another Zimbabwean study, conducted by Hlongwane *et al.* (2014), dealt with building a Credit Score model for individuals using data from existing personal loans, both performing and NPLs. Using regression analysis as well as DA techniques, they argued that correct classification measured effectiveness and concluded that age, purpose of loan, marital status and time spent at the present job were the only characteristics skewed towards failure to service debt. Furthermore, repayment time was also found to be related to age linearly, as well as to marital status and the purpose of the loan. Furthermore, compared to other categories, such as married clients, older people and single borrowers pose a risk to default.

Still in Zimbabwe, Mutava (2015) neither expanded nor developed a new Credit Score model but rather focused only on scoring methods and techniques used by

different institutions, among them Commercial Banks, Merchant Banks, Building Societies and the Post Office Savings Bank. A total of 19 institutions participated in the study, which also examined information sharing, which was then used in the scoring process. The key findings were that the lender should use different scoring methods and techniques for individuals and corporates.

In Tunisia, Abid, Masmoudi and Zouari-Ghorbel (2016) developed a Credit Score model for a Commercial Bank using LR as well as DA. They augmented the study through use of loan amount, amount of loan outstanding, borrower category of the social-profession and loan monthly repayments which should not exceed 40 percent of monthly salary, as the variables. Additionally, borrower credit behaviour variables listed were age, loan amount, outstanding loan and occupational category. The study found and argued that, notwithstanding the limited number of variables, the model may still be efficient when the variables used influence capacity of borrower to perform. Schweser (2013) posited that to attain efficient use or application, the Credit Score model should be characterised by key elements, which include accuracy, transparency and interpretability, as well as fairness and feasibility.

Accuracy means the model should be able to provide insignificant errors and utilise a small number of independent variables. Too many errors may impact the dependent variable indications. The system should obtain prompt results without challenges and at low cost (Schweser 2013). Transparency and interpretability in a model can be measured by a scale, a set of measures that has some value, characteristics and intensity levels, normally expressed by a position, such as a number on the scale. It was concurred by Page and Meyer (2006) that the results produced by the model should be easily found, tracked and interpreted.

Fairness of loan model refers to the non-existence of prejudice, as well as being non-discriminatory, particularly with regard to features such as race, gender, religion, and handicaps, along with ethnicity, which are considered sensitive. The techniques applied by a model should, therefore, be efficient to eliminate unfairness at any given point in time and the loan model should not underestimate or leave a negative legacy when evaluating a prospective client (Schweser 2013)

Feasibility means an effective loan model suits a credit situation when evaluating a client. The loan model should thus be utilised where the bank will be operating from. In addition, a time-frame or valid period for the utilisation of the model in facilitating an appropriate decision, is of essence to the user. Furthermore, the loan model outcome must be secured during the valid period to enable users to refer to any aspects, while benefits of the model must outweigh the costs to exhibit economic efficiency (Schweser 2013).

3.5.5 Evaluation of Durand's Credit Score

The Internal Credit Score model of an institution is customised according to the bank's desirable risk appetite measurements, hence the bank may have more than one Internal Credit Score that could be for personal lending, SME lending, as well as for corporate lending (Gestel & Baesens 2009; Dastile, Celik, & Potsane 2020). The Credit Score is associated with various benefits discussed herein.

A Credit Scoring model:

- enhances client request discrimination, which enables the bank to reduce its future losses before originating and or expiry of facilities;
- the model plays a critical role as decision support tool in credit risk measurement and management;
- through credit Scores, financial institutions achieve better pricing, notably risk-based pricing,
- clients with good credit scores who demonstrate a low risk are rewarded through lower interest rates, while higher risk clients receive higher interest rates;
- a reduction of time in processing new applications (automated) due to instant feedback by the scoring model that enables the bank to process more applications (Berger & Udell 2006; Gestel & Baesens 2009).

Meanwhile, Abdou and Pointon (2011) observed a substantial number of benefits that include, among others; improved customers services and retention of creditworthy customers due to quick turnaround time led by the model; both statistically and significantly correlated variables are used by the model, with repayment performance; and mitigation of bias that would result from judgement

decisions being made by lenders is achieved through use of an Internal Credit Score model. Furthermore, the same data provided by a borrower can be evaluated by any bank lending officer and weights drawn using an Internal Credit Score model; validation of the internal credit model makes them reliable and the models are not adjusted because of gender, race or marital status but are used as they are across the board, while profitability may be achieved on discarding all high-risk clients at evaluation stage.

Several scholars (Sullivan 1981; Bailey 2004; Abdou & Pointon 2011) had the following concerns on the internal Credit Score model;

- The data used evolve, thus, the borrower financial position can change without any warning and various techniques applied lead to different Scores for one client;
- Credit Scores can use any variables or characteristic of a client, notwithstanding its link with repayment and at times, economic fundamentals are not incorporated in the model, which may impact its usefulness;
- It is difficult to incorporate all variables that influence loan repayment as the Score sheet may become so long, Type i and Type ii errors are experienced;
- The model is not standardised and varies from country to country and market to market, even for the same institution, for example, cut-off Score of a commercial bank at a growth point differs from the same bank in the capital city or big town, largely driven by targeted clientele.

The reviewed literature revealed the Internal Credit Score model is utilised by most lending institutions including commercial banks, however, there is insufficient evidence from previous studies that demonstrates that the efficacy period of the model makes it an effective tool. There are also no supporting studies demonstrating that one Internal Credit Score model, when applied by all commercial banks, is considered effective and will mitigate NPLs. The use of historical data on the Internal Credit Score model results in banks lagging in information, suggesting lending decisions may not be informed. Therefore, there is a need to cover this gap with this study.

3.5.6 Measuring Credit Score Model Effectiveness

Miller (2009) proposed some methods of assessing the effectiveness of the Credit Score model. For instance, that this assessment be done by analysing bad loans, correct classification, separation measures and rate and ROC Curve and that all this should be done at the expiry of the loan term because that is when the lender will be able to compare the pre-prediction of loan performance by the model, as well as actual loan performance.

i. Analysis of Bad Loans

Desai, Cook and Overstreet Jr (1995) state that the effectiveness of a Credit Score model can be validated in two main ways: One by analysing the percentage of bad loans correctly predicted by a model, in addition to calculating and identifying a percentage of good and bad scoring. These computations are done after applying various techniques to the model such as LR and DA.

ii. Correct Classification Rate

Correct classification means accurate prediction by the Credit Score model (Samreen & Zaidi 2012). The accuracy rate of client classification demonstrates the effectiveness of the model, as evidenced by the absence of Type i and Type ii errors. Therefore, a Credit Score model with the highest accuracy rate is recognised as the most effective tool.

iii. Separation Measures

Separation measures are also used to validate a Credit Score model (Glennon *et al.* 2007). These measures provide the degree of separation between good and bad performance, as well as accuracy measures. It also notes the degree of difference between the predicted and realised default rates. A generally used Credit Score KS-statistic was proposed by Kolmogorov and Smirnov (1933) to indicate the extent to which a Scorecard separates potential good clients from bad ones. It is a separation measure applied to define the maximum difference between two cumulative distribution functions of good and bad performers and while widely used in North America remains unpopular outside the USA (Anderson 2007).

Determining the KS-statistic is done by first calculating both the good and bad population's cumulative distribution percentage, with the KS-statistic representing the greatest difference between the two distributions. Generally, the range of the KS-statistic lies between 20 and 70 percent, where a value less than 20 percent indicates the model ought to be investigated, while a value of more than 70 percent shows a seemingly over fitted Scorecard (Anderson 2007). The formula used is;

$$\text{KS-Statistic} = \max [ab (CdB - CdG)]$$

Where CdB represents the cumulative distribution percentage for the bad population, and CdG is the cumulative distribution percentage for the good population.

The following diagram (Figure 3.2) shows how a Credit Score model can be assessed.

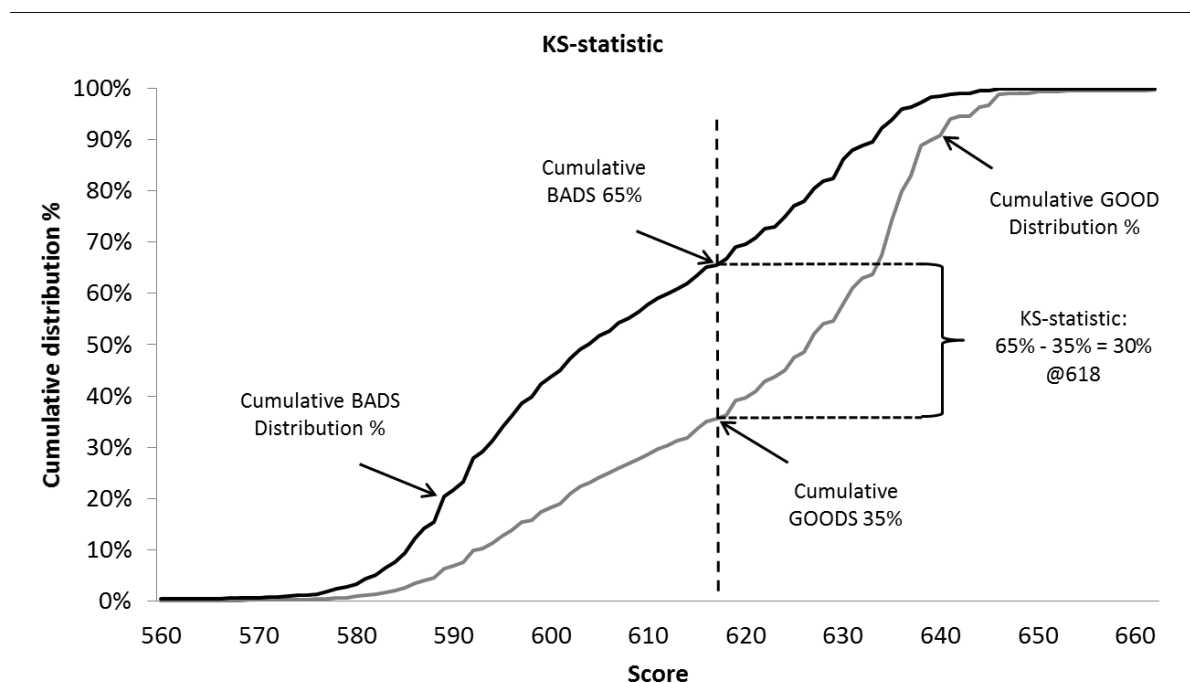


Figure 3.2: KS-Statistic Determination

Source: Anderson (2007)

The combined good and bad population is plotted against the Score (Figure 3.2), illustrating the two distributions' greatest difference between them at a Score of 618. At this Score, the cumulative percentage of poor asset distribution is 65 percent, while 35 percent is the percentage of cumulative good asset distribution. At a Score of 618, the KS-statistic is then given as 30 percent (65–35 percent). A KS-statistic weakness is that it is determined at a single point; which may not represent the expected credit Score cut-off. In addition, whereas other measures are measured over the entire Score range, the KS-statistic is not (Anderson 2007).

iv. Receiver Operating Characteristics Curve

The Receiver Operating Characteristics Curve (ROC) Curve is a statistical method used to measure performance of a classifier such as a Credit Score model (Krzanowski & Hand 2009). It compares the forecasts at inception and the actual output of the model, enabling the lender to view its prediction strength. The ROC Curve thus shows the capability levels of the model. However, the Area under Curve (AUC) represents the degree of separability, which means the basis of the AUROC rests on two concepts, being able to mark true positives (sensitivity) and recognise true negatives (Krzanowski & Hand 2009). The AUROC is determined across the Scorecard's entire Score range. Tan and Phan (2016) and Berg *et al.* (2018) supported the use of ROC after having observed its effectiveness on measuring a Credit Score model.

The following Figure3.3 shows how a Credit Score model can be evaluated.

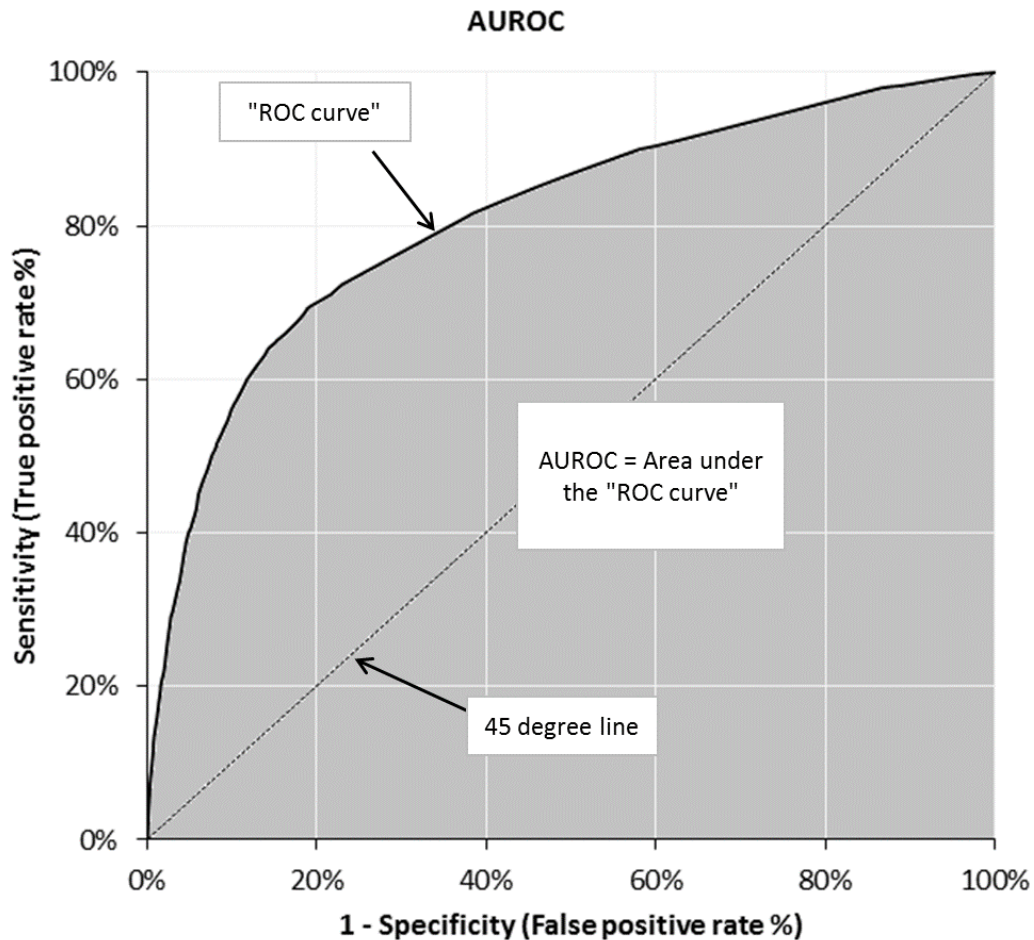


Figure 3.3: Area under Curve for Receiver Operating Characteristic

Source: Kritzinger (2017)

The 45-degree line (Figure 3.3) reflects an AUROC of 50 percent, which represents a “random model”. In order for a Scorecard to be better than a “random model”, the AUROC has to be greater than 50 percent, as a 70 percent or above AUROC is perceived as acceptable, showing model effectiveness (Kritzinger 2017).

The above discussion has shown how the Credit Score model has evolved over time, presenting the manner in which different scholars have approached the process, refining it along the way to strengthen its efficiency and effectiveness in loan application evaluations by individuals and corporates in the different sectors. The review has shown the Credit Score is a quantitative model that initially used DA as an analytical tool. However, in pursuit of a better and more reliable loan evaluation tool, researchers applied more techniques, for instance, probit, linear regression and LR analyses, decision trees, as well as artificial neural networks, and fuzzy

algorithms. The refinement of the model also saw the addition of more variables such as economic conditions, scoring for current customer account, credit limit, and current account identity, as well as account classification, amount revolving and renderability.

3.6 Development of the Z-Score Model

The Z-Score model is the brainchild of Altman (1968), who developed it specifically for assessing the financial position of listed manufacturing companies. He used five ratio categories guided by various fundamentals, such as various alternative functions and their statistical significance. These included determining each independent variable's relative contribution, evaluating relative variables and the inter correlations between them, as well as the need to fully value their relationship towards bankruptcy prediction. Also considered were various profiles' predictive accuracy that drives the accuracy focus of results. The main sources of information for the Z-Score model analysis are financial statements from borrowing clients and ideally, the borrower should be a listed manufacturing company. The information availed is then fed into a system or programme, whereby every financial variable is weighed then summed into a Score. The sample of the Z-Score model consisted of 66 manufacturers with more than US\$1million assets. These companies were listed corporates while half had filed for bankruptcy in the USA.

The five standard ratios used in the Z-Score formula were liquidity, profitability, leverage, and solvency, as well as activity ratios (Altman 1968), with the formula given as follows:

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

Where:

X1 is working capital/total assets;

X2 is retained earnings / total assets;

X3 is earnings before interest and taxes/total assets;

X4 is market value of equity /book value of total debt; and

X5 is sales/total assets.

A brief explanation of each component of the formula is given below.

X1: This is the working capital/total assets, a ratio is used to determine the liquid assets of the borrower in relation to the level of its capital, this being the current assets, less the current liabilities, to determine the company's working capital. Working capital demonstrates the borrower's liquidity position, which enables the borrower to meet daily expenses, as well as monthly loan obligations.

X2: These are retained earnings / total assets, a ratio that applies cumulative returns for investments over a given period, as opposed to debt or equity. The main challenge of using this ratio is that it only favours well-established companies, while new companies register low returns because they would not have sufficient time to generate earnings. As a result, they are likely to be classified as bankrupt.

X3: These are earnings before interest and taxes / total assets, which evaluate the borrowing company's asset productivity. Negative production impacts sales, generating cash flows and used to service the debt. Notably, liquidation occurs whenever liabilities surpass assets, making it necessary to value income generated by assets.

X4: Market value of equity / book value of total debt is a ratio that depicts the market value or the total share prices of the firm. The total debt forms part of the borrower's obligations that can be either short-or long-term. The ratio will also reflect how client assets may decrease in worth before other obligations surpass company assets. As a result, the client will be insolvent, lessening the probability of repaying the borrowed funds.

X5: Sales/total assets is a ratio that reveals the company's asset capacity to generate sales. This is used by the company in comparison to its competition, as a mechanism of determining and comparing industry performance. The formula was interpreted and weights or Scores, which indicate financial status of the borrowing company, were as follows: when a Z-Score is greater than 2.99 the company clearly falls into the "non-bankrupt" category, while those firms that have a Z-score less than 1.81 are all considered bankrupt. The area between 1.81 and 2.99 is known as the "zone of ignorance or the grey area" due to error classification susceptibility. The Z-value Score of 2.67 best discriminates between bankrupt and non-bankrupt firms.

A Multivariate DA method was employed by Altman to analyse the data, where Multivariate DA indicates all statistical methods that analyse multiple measurements simultaneously on each individual respondent or investigated object (McGarigal, Cushman & Stafford 2012). Furthermore, multivariate techniques also allow users to examine relationships among variables in an all-inclusive way so that the relationship between variables can be quantified. The association between variables can be controlled by users through cross tabulation, multiple regressions, and partial correlation, while also introducing different variables to establish associations between the dependent and independent variables or to set out under which conditions the association takes place. Moreover, a picture that is more realistic picture is achieved instead of examining a single variable.

McGarigal *et al.* (2012) have raised some concerns regarding the complexity of multivariate techniques, involving high level mathematics with a statistical data analysis programme. These statistical programmes can be costly for an individual to purchase and statistical modelling outputs are always more difficult than what a layperson can interpret. A large sample is required for multivariate techniques for meaningful results and to minimise the risk of bias.

The Z-Score model was tested using the F-Test, a programmed statistical technique that shows useful predictors in a model (Dougherty 2011). The validation results confirmed that all the variables are noteworthy at the 0.001 confidence level. This shows the usefulness of all variables in their different groups. Furthermore, the F-test is helpful in that it can be used with more than two populations, while its main challenge is that it assumes a normal distribution and thereby provides an inaccurate result when data differs significantly from this distribution.

The 95 percent accuracy of the model makes it more effective in predicting company failure one year prior to bankruptcy. However, its precision decreases from 72-52 percent for a period of two to three years prior to insolvency. The model recorded modest error rates of six percent on both Type i and Type ii errors, thus confirming its usefulness. Use of the model has since been extended from manufacturing companies to other areas such as business loans, investments, and internal control measures.

3.6.1 Analysis of Z-Score Model in Developed Countries

The Z-Score Model has also been challenged by both scholars and practitioners. For example, in the USA, several authors (Deakin 1972; Eisenbeis 1977; Ohlson 1980; Jones 1987; Eidelman 1995; Zopounidis & Doumpos 1999; Shumway 2001; Heffernan 2005; Gopalakrishnan *et al.* 2016; Dondo 2019) determined the model has been an effective tool. Their arguments were on the account of auditors being able to evaluate a going concern status of an entity; the model being a faster and cheaper method of evaluating a company's financial position; as well as the model providing an early warning system for management and investors. Furthermore, the model is precise and facilitates a firm conclusion. The five ratios applied are a standard, which mitigates inaccuracies and judgements. The model can be validated statistically by confirming its reliability as it uses past audited accounts, offering a true trend analysis as opposed to other models that use projections.

Eidelman (1995), however, identified some weaknesses in the model, arguing it cannot be integrated with other models or techniques; it cannot detect manipulated data on financial statements and most financial ratios applied do not have a normal distribution, limiting validity of the Multi DA technique. Moreover, the formula may need to be modified in the absence of market value data and the models' accuracy rate diminishes for longer.

Studies in the USA averred that the shortcomings of the model are as follows:

- the economic environment had an influence on the outcome of the model (Begley *et al.* 1996);
- the model's predictive capability is diminishing compared to its earlier days of establishment (Grice & Ingram 2001) and
- it is also not effective in predicting bankruptcy of companies not in the manufacturing sector.

However, the model was found to be effective in determining financial stress of companies other than bankruptcy. Re-estimation of the coefficients used to discriminate good or bad loans were proposed.

Gritta *et al.* (2008) in the USA employed the model in determining financial conditions in the aviation industry. Their core findings demonstrated that the model can effectively predict financial position in aviation. The effectiveness of the model in the aviation industry was further confirmed by Hsu (2017). Specifically, all the airlines who had positive Z-Scores remained viable, while the airlines with negative Z-Scores eventually filed for bankruptcy a year later; thereby demonstrating effectiveness of the model. Additionally, Hsu (2017) argued the model should be fairly simple to calculate with the data needed for the equation available from the financial reports of a company. The shortcoming of the model is that the market value of a company may not be obtained on non-listed companies. However, the contribution is that the model is ideal for companies listed on the stock markets.

Pongsatat, Ramage and Lawrence (2004), in Thailand, did a comparative study of the Z-Score and the Ohlson (1980) O-Score model, with 120 Stock exchange-listed companies, listed for three years. These scholars found that both models were efficient in predicting future failure of both small and large companies and not listed companies only. Still in Thailand, Puagwatana and Guanawardana (2005) undertook a study on limited companies. Their arguments on the strength of the model were based on modification of the model due to absence of market value data, however, the model went on to produce a 78 percent accuracy in its prediction of financial solvency. This meant a minor adjustment to the variables does not upset the outcome of prediction with high margins.

Testing the model in the Japanese market, Xu and Zhang (2009) argued that although the traditional bankruptcy tools, among them Altman's model, are regarded in the Japanese market, there is a need to consider additional research to determine the best combination of models by, for example, combining it with their own trusted X-Score.

In India, Satish and Janakiram (2011) used the Z-Score model to establish the creditworthiness of customers who wish to access credit terms when buying goods. The authors expressed the model as an effective tool, arguing it facilitates development of a credit policy for a company selling goods on credit and determines appropriate terms. Still in India, Rao *et al.* (2013) undertook another comparative

study of the Z-Score in the manufacturing sector, with the KMV Merton Distance to Default model. They found that the Z-Score model can predict distress of a firm two years in advance, compared to the KMV Merton Distance to Default model, without a fixed period of distress detection. Furthermore, the authors argued that unlike the KMV Merton Distance to Default model, which is greatly depends on equity volatility to determine distress, the Z-Score model does not rely on one variable.

Muminović (2013) conducted his study in Serbia and found the Z-Score model wanting with results found to be inaccurate, which were attributed to the models' coefficients and variables that had remained the same since its development. The need for revised cut off ranges in the model was proposed. In Sri Lanka, Nireesh and Pratheepa (2015) determined that the model successfully established trading companies. A study by Grushniene (2016) in Lithuania (EU) endorsed the model as a main and pragmatic tool for financial bankruptcy prediction, having conducted their study in an agricultural group.

Ashraf, Félix and Serrasqueiro (2019) established that the Z-Score model precisely predicts all different types of firms' insolvency, notwithstanding the stage of financial distress. Ntoug *et al.* (2020) further established that regardless of firm ownership type (family), the Z-score model can illustrate credit risk level. Furthermore, De-Ramon *et al.* (2020) observed that borrowers can be affected by unemployment, presenting a consequently high credit risk, which can be measured by the Z-Score model.

3.6.2 Analysis of Z-Score Model in African Countries

There have been notable studies done in parts of Africa, specifically in SA and Zimbabwe. In SA, Mazaba (2010) hailed the Z-Score model as precise in predicting future failures in investment companies. In Zimbabwe, Mungozha and Ngirazi (2016) established the model as 100 percent effective in predicting bankruptcy of financial institutions one year prior to bankruptcy, as opposed to two years before bankruptcy (80 percent). These scholars, however, pointed out that different results would be found when the model was developed in different economic, social, political and

geographical locations. The predictive value of the model becomes distorted as the prediction time horizon increases.

Dondo (2019) also undertook a study in Zimbabwe and in his key findings confirmed successful use of the model in predicting distressed listed construction companies. The companies themselves, however, were not utilising the model to predict probability to fail. Despite the companies being distressed (40 percent) and in grey zone (60 percent), they continued to operate, suggesting they were not aware of their financial dilemma.

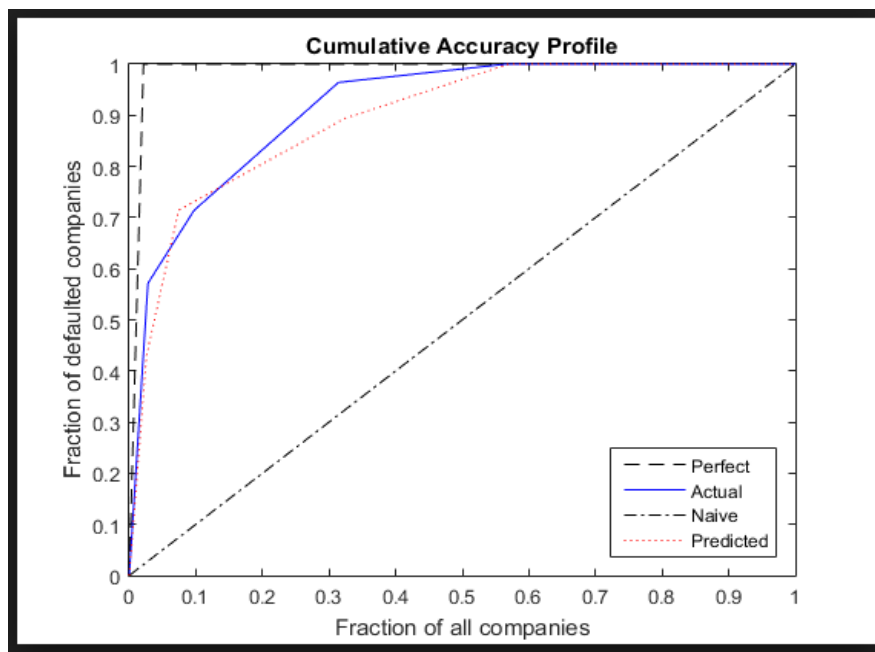
3.6.3 Measuring Effectiveness of the Z-Score model

Banks have used cumulative accuracy, ordinal Scores, as well as regression analysis and ANOVA to measure effectiveness of the Z-Score model.

Cumulative Accuracy Profile (CAP), as Lando (2004) advises, is a tool used to determine quality of loan model prediction, such as a Z-Score model. It is numerically summarised with the accuracy ratio (AR) that indicates how well the model separates firms that are either bankrupt or non-bankrupt. The CAP of a model signifies the cumulative data of positive outlook along the y-axis, versus the corresponding cumulative data of a classifying factor along the x-axis.

The validation of a model's discriminatory power is assessed based on the model features, components and factor level, considering a representative data sample used for model development (validation sample). Most importantly, discriminatory power is likely to be overstated when the model is over-fitted to a particular data set, such as the development sample. The CAP is graphically represented in Figure 3.4 below:

Figure 3.4: Graphical Illustration of a CAP Curve



Source: Anderson (2007)

Figure 3.4 illustrates that the predicted results and actual outcome were slightly different, demonstrating that the model is effective. The predicted results in red colour were just below the blue line, which represents the actual results.

An Ordinal Score is an assigned number that ranks an individual, object or subject on the construct being validated. The most relevant and comparable way to draw a comparison between models that have different sample sets, is through the measurement of their ordinal ability in distinguishing between companies most likely to go bankrupt. The effectiveness of a model is measured by an ordinal Score (Miller 2009). This shows the decay of the model and tests the ordinal Score which measures, over time, a model's ordinal predictive ability. Therefore, the model becomes useless in practice when the signal decays too often.

The formula used to calculate an ordinal Score was developed by Schweser (2013) and was used to measure prediction effectiveness.

Formula to determine Ordinal Score

The sum product of the decile Scores

Ordinal Score formula

10

$$X = \sum_{i=1}^{10} PBK_i$$

$$i = 1$$

$$\text{Where; } PBK_i = \frac{\text{number of companies in decile } i \text{ which went bankrupt within } x \text{ years}}{\text{total number of companies which started in decile } i}$$

The decile score sum product and bankruptcies percentage within a number of x years, are necessary to agree with each decile. The higher the ordinal Score, the better the model's ability to differentiate which companies will, most likely, go into bankruptcy, from those least likely to go bankrupt. This ordinal Score can acquire continuous values from 0, where there is no drift or maximum stability, to 10, where a complete drift or no stability exists.

Schweser (2013: 39) used the below-captioned formula to measure prediction performance, to evaluate credit rules by computing, as well as to measure the number of correctly predicted defaults:

$$= \frac{\text{number of defaults correctly predicted}}{\text{number of defaults}}$$

Therefore, effectiveness is demonstrated by the prediction level, the higher the better. Regression has been used by Meeampol *et al.* (2016), together with ANOVA statistics, to determine the significance of variations, while also used to predict the value of a variable on the back of more than two variables. By contrast, the PHSTAT programme, which is excel-based, outlined the ANOVA summary of an analysis of five (ratios) variables, validating their influence on the Z-Score model. This indicated whether the model is effective or not. In this study, the model successfully predicted the bankruptcy of all 100 companies analysed.

The Z-Score model has evolved from initially being applied to manufacturing firms and has been applied to evaluate other industries, for instance, aviation and the service industry, including banks, retail and construction firms, among others,

including non-listed manufacturing companies, which were excluded before. The five variable formulae have remained in use even though, in some instances, four ratios were used due to data unavailability. There is a mixed view of both the success and failure of the model, where scholars have bemoaned that the cut-off Score should be revised, as the model is not suitable for long tenures and not applicable in all world markets. This means it is imperative to evaluate its applicability in a developing nation such as Zimbabwe, which has been facing NPL challenges since the year 2000 (RBZ 2018).

3.7 Development of the Asset-Based Model

The Asset-Based model is a credit assessment tool that uses ratios as with the Internal Credit Score and the Z-Score models. It can also be used in conjunction with other models, largely due to security requirements on most loan agreements (Orgler 1970). The Asset-Based Model was developed by Orgler (1970), who was motivated by the fact that NPLs were caused by inadequate attention to existing loans in the banks' portfolio.

The development process involved the financial statements of bank clients, where ratios such as the liquidity, profitability, leverage and activity ratios were obtained. The three ratios, namely liquidity, profitability and activity ratios were also utilised by Altman (1968) in the development of his Z-Score model to predict bankruptcy. These ratios were likewise used to analyse the financial status of existing clients in a portfolio by Orgler (1970).

The fourth ratio applied in the Asset-Based model was a Leverage ratio. A leverage ratio measures the current company's debts with financiers (Bessis 2010). A commonly used ratio is the Gearing, which is calculated as total debt/total equity. It shows the capacity of the borrowers' capital to carry additional borrowings or new borrowings.

Orgler used regression analysis, described as a computerised quantitative technique, for information assessment. The purpose was to statistically separate good loans from bad loans. From this analysis, it was found that of all the variables applied, only the secured/unsecured variable had both a positive coefficient and value, which

respectively stood at .1017 and 1.83. The positive coefficient of the secured/unsecured demonstrated that an unsecured client exposes the lender more than the secured client. This indicates such a loan needed security at inception, while it also suggests that when lending to clients, a lender should always have a fall-back position as a source of repayment. Thereafter, the concept has been utilised by many banks globally. Thus, the client's project should be funded when a client has sufficient security that can be liquidated to repay the borrowed funds.

3.7.1 Analysis of Orgler's Asset-Based Model in Developed Countries

Constand, Osteryoung and Nast (1991) analysed the Revolved Asset-Based lending with a 5-year line of credit. What they found was that any mistake on the agreement and security values, creates recovery challenges between the lender and client. Berger and Udell (2002) compared various lending technologies and argued that Asset-Based Lending hinges on statistical financial ratios, security ratios and credit Scores and that the limited number of loans granted using this model, is correlated to a formula linked to the liquidation and worthiness of assets availed as security. The authors proposed that lenders should continuously monitor the values of pledged assets to ensure the loan is fully covered at any given time.

Bakker, Klapper and Udell (2004) conducted their study in Poland, where they compared other lending types with Asset-Based lending. They confirmed that riskiness of a borrower is not a barrier to loan access but the liquidation value of underlying assets is of paramount importance. Contrary to Asset-Based lending, they argued that security is the primary source of repayment; these authors felt that security is, in fact, a secondary source of repayment.

A UK study by Armour (2008) found security enforcement of the Asset-Based model yields positive results. For instance, it leads to debtors being better managed, improving the credit limit and lowering interest rates. Secured lending also influences the ways in which debtors manage and take responsibility of their debt, making the borrowers respect their commitments. Armour (2008) further argued that default risk decreases and improves loan portfolio quality. This was confirmed by Shadab (2014), who studied performance sensitive debt, establishing that the strength of a debtors' base also determines the credit limit.

Several benefits of the Asset-Based Model have been substantiated by arguments listed in the Comptroller's Handbook (2014); it is a measure which avails quick funding to businesses and strengthens their liquidity position, rather than anticipating an injection from debtors, who may fail to perform at the time of need; while it also helps the facility inject immediate key resources, especially to cyclic enterprises that do not generate cash flows perennially and want to boost their stocks. Furthermore, the Asset-Based model enhances optimistic companies by funding their expansion programmes where the bank does not request many covenants, as compared when extending a facility on the back of cash flows. It is also recorded that performance risk can be eliminated by upfront bank charges, solid security and regular call visits to clients. Moreover, Lian and Ma (2019) argued that 20 percent of the USA's loan portfolio is made up of loans evaluated using the Asset-Based model. Loans are secured with physical assets such as inventory, equipment and receivables, which has resulted in small firms battling to access funding because of limited assets.

3.7.2 Analysis of Orgler's Asset-Based Model in Africa

The Asset-Based Model has also been examined by African scholars, with Nyangara (2013) conducting his study in Zimbabwe through an examination of the impact of lending technologies on SMEs. The use of CAMPARI, transactional lending and methodologies such as relationship lending which were in use at the time were examined. The key findings showed that due to a lack of suitable collateral, SMEs were battling to access funding because of the stringent security requirements imposed by the Asset-Based model. The study also argued there was no difference between transactional and relationship lending, as these were Asset-Based, something considered their weakness.

Fatoki (2014) researched financing SMEs in SA. While the Asset-Based model was a key evaluation tool, banks in SA also considered the business plan and set collateral accordingly. In Kenya, Ollows and Moro (2015) studied the use of both transactional and relationship lending in evaluating their SMEs. The findings were that SMEs there have reasonable access to funding and collateral was not a major hindrance. They proposed and argued that use of a combination of the two methodologies could be more beneficial to both parties because they complement each other.

In Ghana, Tague (2016) did not refute Orgler's findings but additionally found the Asset-Based model is a fully secured product and carries low risk. The arguments were anchored by the Commercial Bank having to put strong monitoring and control measures of availed security in place. There are limited agreements on the facility, making it less cumbersome to the borrower. Furthermore, the facility under the Asset-Based model is generally expensive and offers the lender much control over the borrower's cash flows and seizure of security.

3.7.3 Security in Asset-Based Model

Popli and Puri (2014) refer to security as an asset in any form that can be used by a borrower to secure borrowings from the bank. The following are the types of security available to a lender, the debtors' book, stock, and real estate or immovable property, as well as moveable property such as equipment and machinery.

i. Accounts Receivables

Clients' debtors may be placed as security when the lender is granting a loan under the Asset-Based model (Popli & Puri 2014). Furthermore, the bank places its interest on borrowing clients' debtors' book by asking the borrower to pledge or cede the debtors book to the bank. This act should be reduced in writing. Additionally, interest is placed on the strength of the debtors' reputation in the market, for example, on payment of creditors. In the interim, the bank will discount the debtor's book value by between 40 to 90 percent, depending on the risk appetite of the lending institution. For example, when the pledged debtors' book is worth US\$100,000, the bank will calculate 40 percent of this amount, therefore, the maximum loan granted is US\$60,000.

ii. Stocks

The bank considers inventories as security and effects its interest on them (Bijkerk, de Vries, & Casper 2019). This is also achieved through pledges or ceding of stock by the borrower and should be reduced in writing. It will thus be important for the bank to do due diligence and consider stock quality, value, and nature of the stock, for example, perishability and availability of ready customers in the event of disposal.

iii. Real Property

Real estate comes in the form of immovable assets, such as undeveloped land that can be commercial land (big), residential stands, farm, and residential house or apartment (flats or cluster home), as well as high-rise commercial buildings (Smith 2016). Furthermore, these assets should have title deeds, which ought to facilitate registration of a mortgage bond in their favour (in the bank's name). This process is facilitated by lawyers. In addition, the bank will also take custody of the original title deeds, making it impossible for the borrower to sell the property to someone before the loan is liquidated. The immovable assets appreciate and do not expire, making it tangible security with long life (Popli & Puri 2014; Smith 2016).

There are several factors to be considered when the lender sets or stipulates the type of security needed from a borrower. Popli and Puri (2014) as well as Smith (2016) identified marketability; ascertainment value; stability value; transferability and durability as the key considerations to be made when choosing security type.

Marketability refers to the prompt sale of an asset pledged as security. The security should easily be disposed within a very short space of time (Popli & Puri 2014; Bijkerk *et al.* 2019). It is therefore the bank's responsibility to critically analyse pledged security prior to making a lending decision, for example, stock of partially processed goods is likely to be difficult to sell when compared to raw materials or finished goods. Therefore, before accepting any security that will be a source of repayment in the event of default, the bank should ascertain the ability of quick cash flow generation from disposal of the security.

Ascertainment of value means the value of the type of security under assessment obtained using professional valuers in the appropriate field of the pledged security (Popli & Puri 2014; Bijkerk *et al.* 2019). For example, immovable assets are valued by registered estate agents who are expected to possess the required skills, procedures and approaches, such as replacement cost. They apply all these skills in determining property values. Therefore, correct property values obtained by the estate agent enable the bank to ascertain its vulnerability and then set the appropriate cover.

Stability in value means the worthiness of an asset remains constant, notwithstanding changes in various factors that may upset values (Hayes & Elgar 2006). The bank is, therefore, expected to select a security type with a value that may not easily diminish due to unforeseen circumstances, as this will call for frequent enhancement of the security to cover up the unsecured portion of the limit. Furthermore, this suggests security with stable value ensures the bank is secured at any given time.

Transferability and Title mean the ownership of asset or security pledged can be changed from the borrower's name to the bank (Popli & Puri 2014; Cerqueiro *et al.* 2016). Accordingly, transfer of the title takes away the rights of the borrower, as the bank will now have absolute rights and control of the assets (title). Therefore, to successfully effect transfer of ownership, the pledged security should have legal and verifiable documents that prove the asset belongs to the borrower.

Durability means the pledged security has a long life and cannot easily wear and tear (Popli & Puri 2014; Cerqueiro *et al.* 2016). This means the security acceptable by a bank should have a reasonable lifespan that covers the timeframe during which the bank will be exposed; consequently, it can avoid employing security measures that have to consistently be replaced.

Even though lenders have all the above-mentioned security types at their disposal, Caouette *et al.* (2008) have identified some risks associated with the Asset-Based Model. These are collateral risk, collateral illiquidity risk, legal risk and reputation risk.

Collateral risk means that when something undesirable happens to the security pledged by the client, the bank will not be able to recover its money from the borrower. This will necessitate putting mitigation measures for all known risk on the security. For example, most banks ensure stock is fully insured in the event of fire (Caouette *et al.* 2008). Furthermore, Collateral illiquidity means the bank may face difficulties in disposing the pledged security as source of repayment. Therefore, it is important for banks to protect themselves by avoiding taking specialised assets for which it is not easy to find buyers.

Legal risk occurs when the bank may fail to possess due to various reasons, such as change of ownership or selling pledged security to recover their money, while reputation risk means the bank's name may be tarnished should they not follow the legal route in their debt recovery processes (Caouette *et al.* 2008).

3.7.4 Measuring the effectiveness of the Asset-Based Model

Schweser (2013) also developed a formula for testing the effectiveness of the Asset-Based model, which is:

Number of firms that default

Number of firms that did not default

The model is considered effective when there is a great number of assets are performing. Furthermore, the number of write-offs is also used to measure model effectiveness. Alan and Gaur (2012) argued that the number of write-offs is any debt the bank considers unrecoverable. Additionally, the model can be used concurrently or in conjunction with other loan models.

The Asset-Based model review above demonstrates that notwithstanding technological development and globalisation, this model has remained firmly security-based (Caouette *et al.* 2008; Bijkerk *et al.* 2019). It has always relied on security types such as inventory, equipment and receivables, with the main security considerations being marketability, stability in value, transferability and title, as well as durability of the security pledged (Popli & Puri 2014; Smith 2016). Emphasis is also placed on ensuring the contracts entered are water tight, with no legal risk.

3.8 Related or Alternative Loan Models

The following are some of the loan models and or techniques which may also be applied by commercial banks when evaluating commercial loans: Ohlson O-Score model, Zmijewski probit Score model, the Odom and Sharda 1990 model and 5Cs model, previously discussed methods of evaluating their effectiveness are also applied. This work focused on well-established loan models that have been in existence for the past 50 years and carries a sizeable number of variables, for example, Internal Credit Score. In addition, Odom and Sharda (1990) and a

Zmijewski probit Score respectively applied five and three ratios, which were also previously used by Altman (1968) and differ only on technique, suggesting variation on results using the models might not be significant because of application of the same ratios. Subjectivity also relies on the 5Cs; hence, the study did not place much focus on it.

3.8.1 Ohlson O-Score

The Ohlson O-Score was established in 1980 when James A Ohlson developed this technique, motivated by the need to eliminate challenges observed with models such as Multi DA, including; requirements of statistics (two) on the distribution of properties. In other words, equal variance-covariance on both bankrupt and non-bankrupt companies; the Score computed through Multi DA had a low intuitive explanation, which is an ordinary rank. Finally, there was no need to match successful and non-successful companies, as variables should be predictors and not applied for the purposes of matching.

A sample of 105 bankrupt firms and 2 058 non-bankrupt firms with the following ratios applied (Ohlson 1980):

$$O = -1.32 - .407X_1 + 6.03X_2 - 1.43X_3 + .0757X_4 - 2.37X_5 - 1.83X_6 + 0.285X_7 - 1.72X_8 - .521X_9$$

Where, $X_1 = \text{Log (Total assets / GNP price-level index)}$

$X_2 = \text{Total liabilities / Total assets}$

$X_3 = \text{Working capital / Total assets}$

$X_4 = \text{Current liabilities / Current assets}$

$X_5 = 1 = \text{If total liabilities} > \text{Total assets}, 0 \text{ otherwise}$

$X_6 = \text{Net income / Total assets}$

$X_7 = \text{Funds provided by operations / Total liabilities}$

$X_8 = 1 [1 \text{ If net income is negative for last two years}, 0 \text{ otherwise}]$

$X_9 = X_9 = (NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI_t = net income for recent period and t is the number of years. The ratios can be summarised as follows: liquidity ratios (X_3 , X_4 , X_7 and X_8), profitability ratios (X_6 and X_9) and leverage ratios (X_2 and X_5).

The key findings showed factors that significantly impact failure of a company within one year are poor profitability and low liquidity position. Predictive soundness of the model ratio is proven strong on large samples.

Some concerns have also been raised such as the model is very sensitive when it comes to time-frames and that model accuracy declines with time (Grice & Ingram 2001). The model is also not sensitive in each sectorial classification, as well as financial challenges of a firm, therefore, cannot be fully utilised on future financial predictions. Further arguments relate to the usefulness of the model, due to concerns raised including bias due to a selection process that is not non-random (Hillegeist, Keating & Cram 2004). In contrast, Pongsatat *et al.* (2004) argued the model was a much better model compared to Altman's (1968) when predicting bankruptcy.

Similarly, Wang and Campbell (2015) are in favour of Ohlson O-Score model, following its success in predicting bankruptcy of companies in China. While Hensher and Jones (2007) were not satisfied with model performance largely due to its fixed parameters. Meanwhile, arguments from scholars such as Avenhuis (2013) and Kleinert (2014) revealed effectiveness of the model on several occasions in predicting bankruptcy of companies compared to other models. Cenciarelli, Greco and Allegrini (2018) revealed that O-Score efficacy can be strengthened by augmenting the model with parameters correlated to audit data.

3.8.2 Zmijewski probit Score

Zmijewski probit Score was developed by Zmijewski in 1984 with the work motivated by previous studies, such as the Ohlson O-Score, were considered biased, due to over-sampling of distressed firms. The scholar examined 17 studies, with three studies comprised 40 percent distressed firms, while in 11 studies, 50 percent were distressed firms. Zmijewski, however, did not seek to clarify inappropriateness. In the study (1984) a sample of 40 bankrupt and 800 non-bankrupt companies was used, with American companies listed on the New York Stock Exchange for a period covering 1972-1978 comprising the population, while service, finance, and public administration industries were all excluded from the study. The model applied ratios that measure performance, leverage and liquidity:

The Zmijewski (1984) model is formulated in the following way:

$$X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3$$

Where:

X_1 = net income/total assets

X_2 = total liabilities/total assets

X_3 = current assets/current liabilities

X_1 : as the NI/TA can also be referred to as ROA, it exhibits an entity profitability relative to consolidated assets. Therefore, higher ROA is favourable to the company because the company benefits from its assets.

X_2 : TL/TA the ratio validates financial risk posed to the firm; therefore, a higher ratio indicates exposure of the company that will impact its performance in servicing bank obligations.

X_3 : CA/CL, it is a liquidity ratio that determines the capacity of a company to meet its short-term obligations with its assets. Acceptable ratio is 2:1, however, in some industries such as retail, ratios below one are considered good because the company might have negotiated for long-term credit facilities with its suppliers.

The result is classified with a probability cut-off of 0.5, where firms with greater than or equal to 0.5 probabilities were classified as bankrupt, while firms that have a less than 0.5 probability cut-off were classified as non-bankrupt. The Zmijewski (1984) model accuracy rate for the sample of estimation was 99 percent.

Nonetheless, the model is only effective in predicting distress (financial) as opposed to bankruptcy, hence making it imperative for users of the model to comprehend its weaknesses (Grice & Ingram 2001). Furthermore, the model is also time sensitive, consequently, accuracy declines when different time frames are used from those when the model was developed. Similarly, some scholars argued and regarded the model as ineffective due to the use of a single variable and ratios were selected from

prior studies (Shumway 2001; Grice & Dugan 2003). The variables of the model are correlated, and the coefficients are skewed towards bias largely due to use of one regression and failure to test individual coefficients against parameters and absence of paired samples (Platt & Platt 2002; Avenhuis 2013). The Zmijewski probit Score is more efficient compared to other models such as Altman or Springate when analysing listed retail firms (Huda, Paramita & Amboningtyas 2018).

3.8.3 Odom and Sharda Model

The Odom and Sharda (1990) Model is a Neural Network model developed in 1990. In developing the model, five ratios used by Altman (1968) were applied and these are:

X1 is working capital/total assets;

X2 is retained earnings / total assets;

X3 is earnings before interest and taxes/total assets;

X4 is market value of equity /book value of total debt;

X5 is sales/total assets.

The sample was made up of both bankrupt (65) and non-bankrupt (64) firms between 1975-1982 from the same industry and year. The SAS DISCRIM program was utilised and the ratios were computed and entered into both a conventional DA programme and a neural network. Further, a three-layered network was created with five hidden nodes. Convergence was reached after 191 400 iterations and the average time for training the system was approximately 24 hours. The neural network model correctly identified all failed and non-failed companies compared to 86.8 percent for the respective discriminant model (Odom & Sharda 1990).

The model, as with any other neural network model, uses a black box that makes it difficult to comprehend how results are determined and derived in the system (Morris 1997). Furthermore, there is need for full appreciation including a software and hardware appreciation of the entire system, incorporating costs given that some results may not be effective (Atiya 2001). The Odom and Sharda 1990 model was not found among the best models, with regard to excellent accuracy rate when predicting bankruptcy (Tseng & Hu 2010).

3.8.4 5Cs model

A 5Cs model is a simple technique used by banks to determine Creditworthiness of a borrower and is made up of character, capital, capacity, and collateral, as well as conditions (Muhammad & Meleml 2021). These elements are briefly explained below:

Capacity: an extremely important element that reveals company ability to service monthly obligations (Sharma & Pooja Kalra 2015). The lender is guided by borrower history with the bank or other institutions, as reflected by bank statements. Further, a bank may also analyse the cashflows and substantiate them through trend analysis and supporting evidence of projected income, as well as other performance ratios such as Debt Service Coverage, Net profit Margin and Liquidity ratios. However, for a personal loan, spouse income may also be considered as source of repayment (Kabir *et al.* 2010).

Character: It is a subjective evaluation of the personality of the borrower and its main purpose is to confirm integrity and level of trustworthiness (Abbadi & Karsh 2013). Borrower's credit history is analysed for the bank to appreciate commitment and morality of the borrower; this can be achieved through credit references or observance noted during previous loan conducts (Kabir *et al.* 2010).

Capital: banks that provide funding value promoters who contribute to the business, suggesting confidence in their investment, hence the probability of servicing a loan is high (Strischek 2000). Furthermore, it also shows client risk and confidence in their business. A company with a sound financial position, especially capital, displays commitment, optimism and confidence in their line of business (Noradiva, Parastou & Azlina 2016).

Collateral: this is a fall-back position in different formats such as machinery and equipment, debtors, and bonds, which are marketable securities and upon disposal, the proceeds can be used to service the loan (Wilkinson 2013). Importantly, the availed security must have appropriate title, enabling the bank to transfer ownership or register its interest (Sharma & Pooja Kalra 2015).

Conditions: the lender's decision to lend is additionally influenced by environmental factors beyond the bank's control, which entails analysis of the industry, as well as

the economic and political environments (Moti *et al.* 2012). For example, the political situation examines everyday politics such as power and how agency may upset the power balance in a country (Hudson & Leftwich 2014). Therefore, any external challenges that impact debt servicing must be explored.

The model was also criticised by some scholars. There is no standard scoring system and or benchmark, hence each bank has its own Score and some elements are subjective thus, bias may not be ruled out (Muhammad & Melemini 2021). Furthermore, ranking of the elements has no order, suggesting banks should rank the elements according to importance, for example, Character, Capacity, Capital, Condition, and Collateral (Strischek 2000). While Abbadi and Karsh (2013) revealed the need for a geographical impact when ranking the elements. Meanwhile, Melnick (2021) found that a character-based model is more effective compared to traditional models such as that of the 5Cs model.

3.9 Concluding summary

This chapter reviewed literature on the theories wherein the study is based on such as financial intermediation theory, credit rationing theory and portfolio theory among others. Further, development and utilisation of three loan models; namely the Credit Score, the Z-Score and the Asset-Based models, as well as alternative models were discussed. Instances where these models have been applied were outlined, along with these models mainly used for investment decisions by both clients and banks and determination of security, loan limit and accounts grading. The review demonstrated that these models are largely statistical because they use financial ratios and security ratios as variables; the scoring is statistical; and the techniques they use such as probit analysis, DA, regression analysis and fuzzy algorithms are statistical. They are mathematically computer-based techniques that sometimes use human expertise, thus making them extra intelligent in complex classification of borrowers. The statistical nature of the modes enables them to display a precise Score that can be used for fast loan decision-making by Commercial Banks.

While these models are hailed by both practitioners and researchers, they do have some weaknesses. Identified weaknesses include the use of old information from financial statements; difficulty or lack of means to integrate some models with other

models; difficulty of the model to detect manipulated data on financial statements; and that the model's performance can be upset by social, cultural and economic fundamentals.

Details of the research methodology employed to perform this study are set out in the next chapter.

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 Introduction

To undertake this study, certain methodological processes were followed, as detailed in this chapter. The rationale for the methodology, research design, research strategies, and target population, as well as data collection, research instrument, sampling methods, and how data were analysed are all discussed herein. The validity and reliability strategies employed to test the research instrument or data are also presented, prior to concluding with the ethical issues pertinent to the study.

4.2 Study aim

The study's primary aim was to gain an understanding the effectiveness of LPM Models in ensuring sustainable performance of the Commercial Banks; in other words, to mitigate bank closures in Zimbabwe that resulted from a high number of NPL.

4.3 Overarching research question

From the above stated aim, a research question that guided the study was formulated as: To what extent and in what manner is loan performance of Zimbabwean Commercial banks impacted by Loan Portfolio Management Models.

To answer this question and ensure the research problem was addressed, the main research question was divided into the sub-research questions below:

- 1) Which LPM Models are used to predict loan performance?
- 2) Which parameter attributes do the commercial banks in Zimbabwe consider in LPM model development?
- 3) What are the methods and means Zimbabwean commercial banks employ to measure effectiveness of a loan model as lending tool?
- 4) Do LPM Models separate potential non-performing loans at evaluation stage?
- 5) What motivates the Bank to change a LPM Model to enhance effective evaluation of applicants?

4.4 How the research questions were dealt with

The way the sub-research questions were attended to is set out (Table 4.1) below, detailing the type of data obtained, key theories that informed the study, and the calibre of respondents from whom information was obtained.

Table 4.1: Analysis of Research Questions

Research Question	Type of Data Sought	Key Theories	Data Sources	Any Notes
Which loan Portfolio Management Models are used in the bank to predict loan performance?	Qualitative- names of models under use for example Internal Credit score, Z Score and Asset Based model	Portfolio theory, Credit rationing theory and lender theory	Credit specialist from both failed banks and existing banks	Practitioners work experience guided them to respond both questionnaires and interview questions
Which parameter attributes do the Commercial Banks in Zimbabwe consider in loan Portfolio management model development	Qualitative- list of parameters for example clearance, bank report Quantitative- weighing of parameters: percentage, scores	Portfolio theory, Credit rationing theory and lender theory	Credit specialist from both failed banks and existing banks	Credit specialist confirmed and availed parameters under use and how they are weighed
What are the methods and means Zimbabwean commercial banks employ to measure effectiveness of a loan model as a lending tool	Quantitative- numbers of bank financial statement Qualitative- notes on bank financial statements and feedback from interviewees	Financial Intermediation Risk and Credit Risk Credit Scoring	Published Financial statement Feedback from Credit specialist interviews RBZ Monetary Policy statements 2009-2018	Some clarifications were sought from Credit specialist on how they compute the loan model effectiveness

Do Loan Portfolio Management Models separate potential non-performing loans at evaluation stage	Quantitative- number of bank financial statement Qualitative- notes on bank financial statements and feedback from interviewees	Credit Score model Score model	Published Financial statement Feedback from Credit specialist interviews	Published Financial statement Feedback from Credit specialist interviews
What motivates the Bank to change a Loan Portfolio Management Model and enhance effective evaluation of applicants in a portfolio	Qualitative - circumstances which influence banks improve loan portfolio Quantitative - statistics on NPLs or number of bank failures.	Financial Intermediation	Credit Managers or specialist	Banks are guided by quality of loans to determine effectiveness of their loan portfolio management

4.5 Hypotheses

The fourth objective required that hypotheses be developed because there was a need to test the influence of the LPM Models on loan performance. The resultant hypothesised model is illustrated (Figure 4.1) below:

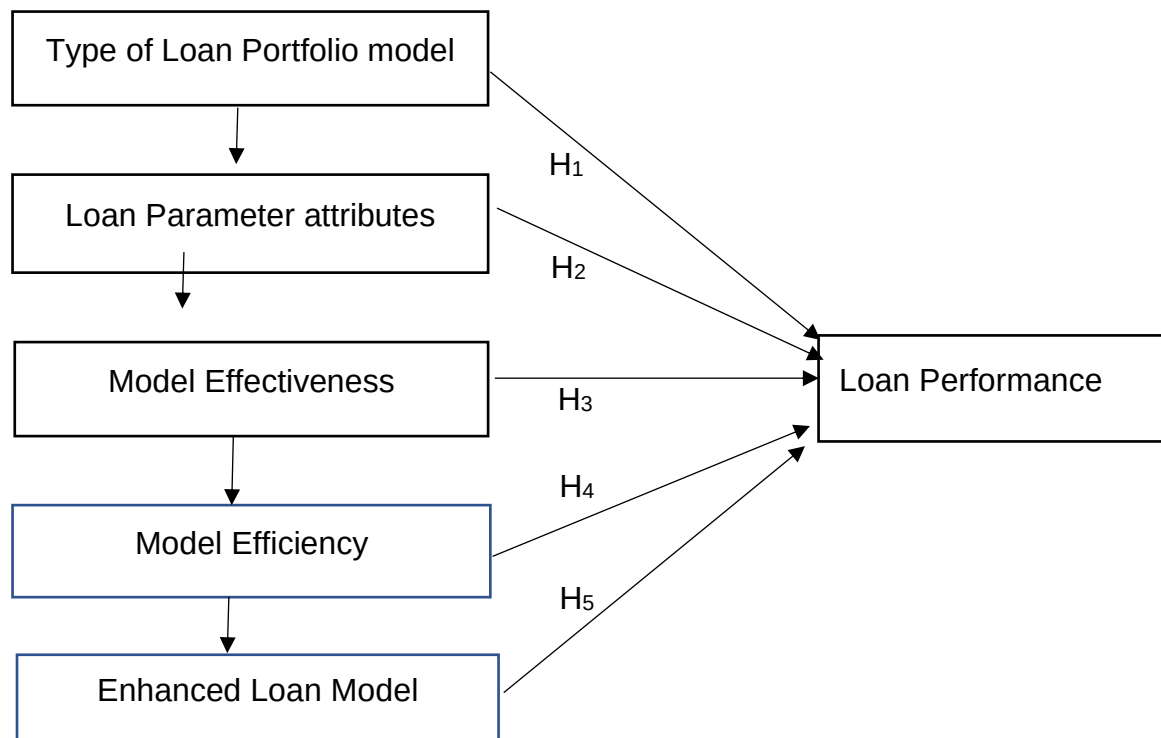


Figure 4.1: Hypothesised model

Source: Developed by researcher based on the fourth research objective

4.5.1 Motivation for the hypotheses

Muijs (2004) advises that a hypothesis for research can be refined from the objectives set for a study and is a form of inferential statistics that allows a study to draw a conclusion about the entire population, based on a representative sample. In this work, the hypotheses determine the existence of a significant relationship, if any, between certain factors and loan performance.

H₁: The type of Loan Portfolio Management Model used has an impact on loan performance

The proponent of the Internal Credit Scoring model, according to Durand (1941) states that the model has an influence on loan performance, however, the significance of that influence was never tested. Samreen and Zaidi (2012) concur, having applied this model in Pakistani Commercial Banks. Nonetheless, Altman (1968) supported the impact of the Z-Score Model, particularly for listed manufacturing firms. This hypothesis tests which type of model has the most significant impact on loan performance, particularly in the Zimbabwean context.

H₂: The Loan Portfolio Management Model parameter attributes used have an impact on loan performance

Rosch and Scheule (2007) contend that parameter attributes in a loan model, as recommended by Basel ii (Basel Committee on Banking Supervision 2004), do influence loan performance. However, the view from Mohamed, Muturi and Samantar (2019), is that there are other factors that influence loan performance, such as educational level of borrowers; other income; business experience and maturity period of a loan. There is, therefore, a need for this study to test the strength of parameter attributes on loan performance.

H₃: The Loan Portfolio Management Model effectiveness impacts loan performance

It is posited that the effectiveness of a loan model is based on its accuracy rate and lowest error (Samreen & Zaidi 2012; Zaidi & Sarwar 2013; Hlongwane *et al.* 2014; Mutava 2015). The veracity of this statement is tested through this hypothesis.

H₄: The Loan Portfolio Management Model efficiency impacts loan performance

There is agreement that efficient loan models impact loan performance, making it necessary to test the extent of significance in Zimbabwe (Cowan & Cowan 2006; Aduda, Magutu & Wangu 2012; Samreen *et al.* 2013)

H₅: Enhanced LPMM impact on loan performance

Mwengei (2013) reasons banks have to consider all internal factors leading to NPLs in earnest, in addition to the NPL impact the overall performance of the bank. According to Louzis *et al.* (2012), distinctive features of each particular bank's loan model, relative to their efforts to maximise risk management efficiency and improvements, are likely to decisively influence loan performance evolution, requiring other factors be tested.

4.6 Rationale for the Methodology

Methodological assumptions reveal how information will be obtained from the target population (Botma *et al.* 2010) and incorporates different procedures and processes, logically undertaken by the researcher (Kothari 2014). The study applied more than one methodology, that is; deductive, based on a quantitative approach that ensured

the data collected was not subjective, manipulative and independent from human feelings (Bryman 2012). This method was additionally chosen on the advice of Borrega, Douglas and Amelink (2009), who state that this method also provides data informed by the problem, which then facilitates generalisation of the findings through statistically proven empirical evidence.

The deductive method, based on a quantitative approach, has merits on validity, reliability, replication, and generalisation, which are valuable for the quality criteria of the study (Bryman 2012). The second methodology used is inductive, based on a qualitative approach and achieved through interviews, wherein experts in the field were interviewed and shared their experience, both from operating as well as from closed banks (Creswell 2014). Clarification was sought to some questions.

4.7 Research design

A wide-ranging design that elucidates the feasible way to accomplish a research study. The design aids as a framework that guides the research on the collection or sources of information, data gathering instruments and how data analysis should be undertaken (Jancowicz 2005; Phelps, Fisher & Ellis 2007; Babbie & Mouton 2011). Sekaran and Bougie (2016) describe a research design as a plan developed to facilitate data collection, measurement, and analysis. In research, the different types of research designs include descriptive, causal, as well as sequential explanatory design, among others (Page & Meyer 2006; Guest & Flammig 2017).

Descriptive research is used to gather parameters a study may use to describe and generalise the outcome of an investigation on a larger population, based on the attributes of the sample population (Malhotra 2010). Causal research aims to establish relationships between variables. Therefore, it is applied when the study aims to use experiments to control variables (Malhotra 2010). This study made use of Sequential Explanatory design, because it involves data collection analysis that is both quantitative and qualitative. It is largely meant to augment, refine, elaborate, and provide explanations of quantitative findings (Bryman & Bell 2015). Sequential Explanatory designs are mostly adopted when the researcher finds the need to use qualitative analysis to help provide details or build on initial quantitative data (Bryman & Bell 2015; Creswell 2014), as was the case in this study.

4.8 Research Philosophy

As a wide observation of the topic being studied, research philosophy consequently considers how the research is to be undertaken, which could either be statistically or in a qualitative manner (Taylor, Kermode & Roberts 2006). Saunders, Lewis and Thornhill (2009) regard a philosophy as a technique of comprehending a study globally and links it to creation of knowledge in relation to the study. It may, therefore, be referred to as how knowledge is developed and interpreted. There are two broad, prominent philosophies in research: Positivism, which uses quantitative strategies, and Phenomenology, which is qualitative in nature (Creswell 2009).

4.8.1 Positivism

A positivist paradigm refers to the existence of a reality that just needs to be uncovered and it can be measured during the study (Creswell 2009). Consistent with this, Neuman (2011) opines that positivist researchers settle for statistical data and make use of surveys or a questionnaire, which are self-completed with results in numerical format. A study through positivist methods seeks a comprehensive analysis using scientific methods that are detailed, can be verified and are applied to unpack objectives. Furthermore, the approach eliminates interaction with participants, thereby facilitating an unbiased and truthful study. The strategy associated with positivism is quantitative, which may utilise surveys, experiments, action research and ethnography.

4.8.2 Phenomenology

Phenomenology or Interpretivist philosophy refers to a qualitative study that pays attention to individual or group lived experience in a certain confinement or within the world (Bryman & Bell 2007). The analysis of data is therefore subjective, due to much reliance on other people's knowledge on the subject matter (Creswell 2009). Therefore, phenomenology attains its research objectives through examining past experiences of an individual, for example, receiving expert insights from experienced personnel. Human beings are considered paramount in constructing a reality, hence, differences in humans facilitate the shaping of new knowledge (Saunders *et al.* 2009).

4.8.3 Pragmatism

Pragmatist philosophy refers to a system that concedes to use of a wide variety of means by researchers in interpreting the world because the probability of several realities is high (Saunders *et al.* 2016). Furthermore, it (philosophy) is not aligned to one strategy but complimentary strategies, which can avail appropriate answers to research questions. Creswell (2014) advises that pragmatic philosophy ascends out of situations, actions and consequences, as opposed to antecedent conditions associated with other philosophies and argues that a pragmatic approach is linked to mixed research methods because it is not aligned to one philosophy.

The nature of the problem under study requires a broader understanding, which augurs well for the adoption of a pragmatic view. Loan models under study are numeric and positivist studies settle for precise data, a deductive approach which is quantitative and makes use of hypotheses and theories (Creswell 2009). Therefore, this work is guided by a pragmatist philosophy because pragmatism facilitates using mixed methods, comprised of data collection methods that are both quantitative and qualitative (Saunders *et al.* 2016). Using a combination of different methods would offer the best insight, as the problem is real and practical.

4.9 Research Strategy

According to Creswell (2009) and Bugembe (2018), there are different approaches used, namely quantitative, qualitative and mixed methods strategies. For comparison and analysis of different variables, quantitative research depends on measurement. Qualitative research, in contrast, makes use of qualifying descriptions or words to record world aspects. At times, it becomes necessary to combine the two approaches to complement each other, resulting in a mixed method. These are explained hereunder.

4.9.1 Quantitative Method

The quantitative strategy stems from a positivist philosophical expression and data are collected through the use of natural sciences (Creswell 2009; Bugembe 2018). It is a data collection method that deals with systematic measurement, statistical analysis and experimentation methods of things that can be counted (Fox & Bayat 2007). Teddlie and Tashakkori (2009) further explain a quantitative study is a method

that needs procedures that are mathematically defined, allowing the researcher to estimate population characteristics within a small margin of error. A method that starts by employing concepts, which are then theorised, is referred to as a quantitative research method (Flick 2011). The backbone of a quantitative method is numerical data.

There are various approaches used in quantitative research, among them surveys, experiments, action research and observation studies, with the main aim of predicting, confirming, validating and testing a theory (Leedy & Ormrod 2010).

A survey is a method of data collection from a sample that provides a statistical description and displays trends, attitudes, as well as opinions (Creswell 2009). There are many variations of surveys, among them being door-to-door interviews, mail surveys and telephone interviews and, at times, computer-assisted interviews, with a questionnaire the most used instrument to collect data (Check & Schutt 2012).

Another method is a cross-sectional survey, which involves data collection from participants, once, during a specific timeframe (Denscombe 2010). The survey research method is normally used where large volumes of data are involved and is a method associated with statistically rated elements.

Experimental research investigates whether the study may achieve a satisfactory result after applying a treatment to an isolated group and compares the results with the other group that was not isolated (Creswell 2009). The subjects are exposed as per given treatment and results observed to see the influence of the treatment.

Action research is achieved through behavioural observation and description on the action shown by an individual under study (Denscombe 2010). This is motivated by the need to solve a precise problem and results will, therefore, be used to craft a manual that contains what is acclaimed as best practice.

Ethnography pays attention only to one particular grouping, for example an organisation or community, and observes prevailing perceptions, social interactions, as well as their behaviours, to obtain an understanding of a chosen group's views

and actions (Reeves, Kuper & Hodges 2008). This is achieved through observations and interviews, which facilitate analysis of their living conditions and social belongings.

Benefits of utilising a quantitative research method are summarised as (Creswell 2009; Wilson 2010; Bryman 2012) a structured research approach that is systematic and precise, with a sample population that produces measurable intuitions into performance, incentives and assertiveness towards the study matter. The method does not allow interacting with participants, unlike other methods, thus eliminating bias, with an extensive sample, notwithstanding limited resources and, thus, seen to be a more affordable data collection method. The statistical nature of a quantitative method facilitates measurement of model effectiveness; which is impossible to do in a non-numeric approach. Moreover, consistent procedures associated with quantitative research, aid validity, reliability and replication, which strengthen the superiority of the research.

With all its accolades, the quantitative research method still has weaknesses, such as being feasible only with large numbers, in numerical form, as well as facilitating an informed statistical analysis. Statistics is considered challenging, which challenges an ordinary person to understand the study (Grant *et al.* 2017).

4.9.2 Qualitative Method

A qualitative strategy stems from the phenomenological or interpretivist philosophical stance. Qualitative research refers to a data collection method that is non-numerical, such as observation, document review, interviews, as well as focus group discussions, among many others (Samkin & Schneider 2008). The main aim of qualitative research, therefore, is to explain, interpret and build a theoretical phenomenon, accompanied by advantages such as clarification by participants on their opinions, and facial expressions that can demonstrate whether respondents are interested in taking part in the study, as well as being honest. The main strategy disadvantage is it takes much time, making it expensive, while there is also room for bias (Zikmund *et al.* 2013).

Documentary analysis means examining, or thoroughly reading any written documents, or listening to previously recorded material not meant for the purposes of the current study. On the one hand, the inquirer thoroughly examines the available documents and can draw some conclusions relating them to the current study (Zikmund *et al.* 2013). On the other hand, a focus group discussion is a dialogue or an interview of a large group of people, possibly between six and eight in number, with the conversation recorded for future transcription. The conversation is held with people that have the same characteristics pertinent to the phenomenon being studied, and they should all be of shared experience or views (Zikmund *et al.* 2013).

Observation is when the researcher observes the phenomenon under study practically, for example, utilisation of equipment. The work process is observed and issues are clarified by users. This method facilitates coverage of reality examination, resulting in an informed decision (Zikmund *et al.* 2013).

An interview is a purposeful discussion undertaken by at least two people or more, with the aim of gathering detailed information on the subject matter under investigation (Zikmund *et al.* 2013; Bryman 2016). Additionally, the interview may be structured, semi-structured or unstructured, prompted by the research objective. The researcher makes an appointment to meet the participant at a convenient location and time and there is an opportunity for clarification of issues under discussion by both parties (Zikmund *et al.* 2013). The semi-structured interview format is generally preferred as the researcher is able to clarify unclear responses through follow up, to uncover additional information (Bryman & Bell 2015), with this probing concept common in qualitative research. As the interviews conducted were of a semi-structured nature, it allowed respondents to answer specific questions, while the researcher could enrich the information from responses by probing those that were unclear. The interviews aimed to gain a comprehensively detailed account from respondents about the problem under study and their experiences thereof.

In this work, senior managers were interviewed in-depth, as the researcher required detailed information regarding experiences and viewpoints of participants on a specific topic (Turner 2012).

The following strengths are offered by this information gathering method: suitable to measure attitudes and most of the other content of interest; allows probing by the interviewer; can provide in-depth information; allows good interpretative validity; relatively high response rates are often attainable; useful for exploration and confirmation (Johnson & Turner 2003).

The following are considered weaknesses of interviews; time-consuming; may only be conducted at the interviewees' convenience, time and location; and opportunity for clarification and probing but the interviewee may not be forced to answer (Cooper & Schindler 2011).

4.9.3 Mixed Method

This research method is referred to by Zikmund *et al.* (2013) as a design that makes use of a strategy that is both quantitative and qualitative for data collection and analysis. Depending on the subject matter, the combination strategy employed in this method, in making use of a questionnaire and interviews for the process of data collection can be very useful (O'Leary 2014). Several authors (Miles, Huberman & Saldana 2014; Saunders *et al.* 2009; Creswell & Poth 2018) provide the merits of a mixed method approach as follows: outstanding advantage is complementarity; utilisation of two methods that complement each other on various aspects being investigated (Saunders *et al.* 2009). Nonetheless, Miles *et al.* (2014) state analytic results are reinforced by the genres, while widely divergent views may call for further re-examination of the conceptual framework (Venkatesh, Brown & Bala 2013).

This makes it imperative to consider the drawbacks to mixed method research, including that: it is considered very demanding and expensive; requires wide skills that enable the researcher to analyse or interpret both quantitative and qualitative data obtained; sufficient time is needed to plan and timeously complete; and some discrepancies may be difficult to correct (Saunders *et al.* 2009; Miles *et al.* 2014; Schoonenboom & Johnson 2017).

4.9.4 Research Strategy for this study

Following the advice of Saunders *et al.* (2009), corroborated by Creswell (2014), this study adopted a mixed methods approach, which demonstrated its ability to provide

an integration of both quantitative and qualitative designs, wherein data were merged, embedded and / or connected. Both different data types were continuously collaborated and integrated (Miles *et al.* 2014; Hackett & Strickland 2018). Taking the advice of Saunders *et al.* (2009) and Creswell (2014), data collection procedures were implemented concurrently, without combining the two. The mixed method employed helped to compensate for any deficiencies emanating from either quantitative or qualitative method, resulting in findings of broad data.

For the qualitative data, various methods such as informal discussions, semi-structured interviews, interaction with bankers to collect primary data, and reviewing of documents to gather secondary data were used. The interviews provided information that offered an insight on how Commercial Banks had utilised Loan Portfolio Models. The respondent diversity selection was intentional and their input very helpful.

All interviews were accomplished at the interviewee's workplace and/ or neutral locations where necessary. The interview setting allowed respondents to share views freely in familiar surroundings, giving them a 'home advantage' in their perception of being in command of the entire interview process; termed. Audio from interviews was captured through a recorder, while an interview guide/schedule provided structure. Interviewees were assured all information collected was purely meant for research purposes.

For the quantitative aspect of strategy, a structured questionnaire was used and non-performing ratios, financial statements of banks, weighing scales of models, and number of closed banks, as well as merged banks, contributed to quantitative data gathered.

4.10 Target Population

People with knowledge of the desired information that can answer the study's measurement questions, namely all participants of interest to the study, are referred to as the target population (Cooper & Schindler 2008; Rasinger 2013). For an investigation to achieve its objective there must be a representative sample of the

target population, suggesting that when data are collected from the wrong population, results obtained are deemed incorrect or invalid.

The target population for this study comprised lending personnel in 14 institutions offering Commercial banking lending services in Zimbabwe's ten Provinces. The lending personnel were Credit Managers, Risk Managers, Relationship Managers, and Credit Analysts, as well as Risk Analysts and Relationship Officers. The ten Provinces were Bulawayo (BYO); Harare (HRE); Manicaland (MAN); Midlands (MID); Matebeleland West (MW); Matebeleland East (ME); Mashonaland East (ME); Mashonaland South (MS); Matebeleland North (MN) and Matebeleland South (MS).

Interviews were conducted with senior risk officers in existing banks, as well as credit specialists from collapsed banks. On the one hand, officers from the existing banks broadly shared their experiences with current models and how these have contributed towards quality assets in bank loan portfolios. In addition, room for improvement was also discussed. This was not possible using a quantitative strategy method. On the other hand, risk officers from collapsed banks were critical in this study because they also shared their banking experience, what really transpired, the prevailing business environment and suitability of the loan models under study during the period under review.

Respondents interviewed for the qualitative aspect of the study are detailed in Tables 4.2 and 4.3 below.

Table 4.2: Existing Financial Institutions' Interviewees

No of banks	Designation	Number of Interviews	Place of Interviews	NOTES
12	Senior Risk Officers	1	Harare	Participants were drawn from small, medium and large commercial banks

Table 4.3: Failed Financial Institutions' Interviewees

Closed Bank No	Designation	Number of Interviews	Place of Interviews	Notes
1	Chief Risk Officers	1	Harare	N/A
2	Senior Credit Manger	1	Harare	N/A
3	Head-Credit manager	1	Harare	N/A
4	Divisional Director-Risk management	1	Harare	N/A
	Divisional Director-Corporate Banking	1	Harare	N/A
6	Relationship Manager - Corporate Banking	1	Harare	N/A
7	Manager-Risk Management	1	Harare	N/A
8	Senior manager-Corporate Banking	1	Harare	N/A
9	Head-Corporate Banking	1	Harare	N/A
10	Head-Credit Department	1	Harare	N/A

Representation of the target Banks in all the Provinces (Table 4.4) is shown below (Commercial Banks Annual Reports 2017). A dot indicates the bank branch in the province where participants were selected. The selection process was done in an inclusive manner, notwithstanding the geographical location and dispersment of the Branches.

Table 4.4: Provincial spread of Banks

Bank name	BYO	HRE	MAN	MID	MC	MW	ME	MAS	MTN	MTS
Agribank	•	•	•	•	•	•	•	•	•	•
BancABC	•	•	•	•	•	•	•	•	•	•
CBZ	•	•	•	•	•	•	•	•	•	•
First Capital Bank	•	•	•	•	•	•	•	•	•	•
FBC Bank	•	•	•	•	•	•	•	•	•	•
Ecobank	•	•	•	•	•	•	•	•	•	
Metbank	•	•	•	•	•	•	•	•	•	•
Nedbank	•	•	•	•		•	•		•	•
NMB Bank	•	•	•	•	•	•		•		
Stanbic	•	•	•	•	•	•	•			•
Standard Chartered	•	•	•	•	•	•	•	•	•	•
Steward Bank	•	•	•	•	•	•	•	•	•	•
ZB Bank	•	•	•	•	•	•	•	•	•	•
CABS	•	•	•	•	•	•	•	•	•	•
POSB	•	•	•	•	•	•	•	•	•	•

Source: Banks Annual reports (2016)

4.11 Data Collection Methods

As indicated earlier, data was collected using both quantitative and qualitative strategies.

4.11.1 Quantitative data collection

A structured questionnaire was used to gather quantitative data through closed-ended statements (Appendix 2a). Connaway and Powell (2010) assert that a questionnaire is a document carrying questions and scales (means of categorizing data) pertinent to the studied subject matter or an organised system of gathering data. This is supported by McGivern (2013), with Zikmund *et al.* (2013) who advise of the need for proper design, selecting questions that answer the objectives of the study and making use of appropriate wording before data collection begins.

The construction of the questionnaire, in being interesting and easy to complete, motivated respondents to be part of the study. A covering letter (Appendix 2b) explained the research purpose, seeking respondent consent and assuring them of confidentiality. The letter included an appeal to respondents for correct information in questionnaire completion.

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 answer 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 (Wild & Diggines 2011). 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 (Cameron & Price 2009).

Wild and Diggines (2015) put forth some advantages of using a 5-Point Likert Scale, namely that respondents are given a wide selection to choose from, each item can be analysed independently to determine participant attitude, thus enabling the researcher to add all participant scores per object, and is able to draw a conclusion. However, some disadvantages can be encountered when using a 5-Point Likert Scale, including that there will be no clarification on the selected answer; participant

answers are only confined to the availed scales, and there is a probability of participants sharing answers. The questionnaire was divided into five sections from Section A to Section E, with a 5-point Likert Scale ranging from Strongly Agree, Agree, Neutral, and Strongly Disagree to Disagree.

Section A sought to capture the demographic information of respondents to establish whether they were indeed the appropriate respondents to the subject matter. Race and age were not included in the questionnaire because, as a matter of policy, the banks do not discriminate in these areas.

Section B covered 12 statements that sought responses on the application of LPM, which was the first study objective.

Section C consisted of eight statements, aimed to deliberate on the model parameter attributes, a second research objective.

Section D comprised 13 statements that aimed to establish the effectiveness of loan models and loan performance. This was the third research objective of the study.

Section E contained seven statements that sought to obtain information on the enhancement of LPM.

4.11.2 Sampling procedure

Prior to questionnaire distribution, a sampling procedure was undertaken, which differently stated, refers to the process of selecting participants for a study from a target population (Yates 2008; Connaway & Powell 2010; Goraseb 2017). The main accomplishment of sampling is to determine full representation of the population by a sample, in other words, a small population set that can be chosen to be representative of the entire target population, from which to generalise results (Sekaran & Bougie 2016).

Of the two broad sampling strategies, that is, probability sampling and non-probability sampling, with the former used for collection of quantitative data. Probability sampling is where the selection of all elements is known and sample members are chosen in

a purely random selection, from the target population (Yates 2008; Wegner 2012). This method uses a variety of sampling techniques, examples are: simple random sampling - applied in situations where, in all cases, there is a uniform population; cluster sampling - wherein common characteristics are shared elements; and systematic sampling - applied to a large population, leading to unit selection in series, as set by a system that was predetermined (Wegner 2012).

Another sampling technique, stratified sampling, involves apportioning the target population into sections, also referred to as strata, with participants randomly selected from these respective sections (Lohr 2007). This technique is used, according to Wegner (2012), when a heterogeneous population is assumed, regarding the random variable being studied, as it was in this case. Division of the population into strata ensures each stratum's population members are relatively homogeneous. It is for these reasons that stratified sampling was used and the following process followed:

Step 1: A list of Commercial Banks that remain in operation, including the provinces in which they are represented, was obtained from the RBZ.

Step 2: To ensure representability of the banks in the said provinces, a list of 15 Banks was prepared.

Step 3: A letter requesting a list of the target participants, which were all the levels of personnel involved in lending activities, was sent to the CEOs or Bank representatives of the 15 Institutions (Appendix 5). In this letter, the CEOs or Bank representatives were requested to split the personnel into Managers and Operational personnel. These became the two strata for sampling purposes.

Step 4: A database of 500 employees was received from all the Banks. Even though statisticians recommend a minimum sample size of 100 respondents is sufficient to undertake a reliability test and factor analysis in a quantitative study (Field 2009; Pallant 2010), it was decided that more responses should be sought.

Step 5: Boxes were obtained and labelled with the names of the 15 participating banks and their provinces.

Step 6: In line with the number of personnel supplied by the Banks, the questionnaire was inserted in envelopes marked either “Managerial” or “Operational”. These envelopes were put into the boxes.

Step 7: The above step thus used convenience sampling. The research assistants were then ready to deliver and collect the questionnaires. However, one of the Commercial Banks was subsequently not co-operative and was not included, leaving 14 participating banks.

4.11.3 Qualitative Data Collection

Use was made of semi-structured, in-person interviews of selected senior employees from existing and failed Banks in Zimbabwe to obtain qualitative data, aided by an interview guide/schedule. This guide (Appendix 2) was designed in line with the structured research questionnaires.

A non-probability sampling technique, purposive sampling, was employed to collect qualitative data, largely through interviews. Purposive sampling mitigates random selection of participants but strategically selects sampled participants who are key, relevant, and able to respond to questions sought by the study (Bryman & Bell 2015). In this study, only risk specialists were considered as most appropriate participants in the qualitative phase, because they have the skills to manage credit risks that impact LPM. This approach resonates with Kumar (2005), who alluded that judgement by the researcher plays a key role in selecting the most appropriate participants. In addition, Leedy and Ormrod (2015) concur that the success in purposive sampling depends on judgement made by the researcher on sample participants.

A total of 24 participants were interviewed, of which 12 were risk officers from existing banks, while the balance was from failed banks. The sample number of participants was guided by recommendations from Onwuegbuzie and Collins (2007) and Teddlie

and Tashakkori (2009), who argued that any number ranging between six and 24 is sufficient or a good representative number of participants for interviewing in a study.

4.12 Pilot study

Before the questionnaire could be widely distributed, it was necessary that a pilot study be done first. This involves pre-assessment of a questionnaire, as well as the interview schedule, in addition to any other data collection method, by means of a small respondent group, similar to actual research participants, to gauge its effectiveness (Saunders, Lewis & Thornhill 2012; Ismail, Kinchin, and Edwards 2018). The pilot test, therefore, analyses the research prospects, suggested research methodology appropriateness and questionnaire coherence. All problems that can arise are identified and attended to prior to the actual study, with correction of any research instrument weaknesses.

The pilot study was done before commencement of field work with a group of 30 lending personnel at a conveniently selected Bank in Harare. This took place after a training session of these officers, an arrangement that had been made with the Human Resources Manager of the Bank. The limited personnel (30) were considered as a sufficient number which could demonstrate efficacy of the research tool. Also, having a bigger sample for the pilot would have impacted into the target population. Meanwhile, scholars also recommend a limited number of 12-35 respondents in a pilot study (Saunders *et al.* 2009; Saunders *et al.* 2012; Saunders *et al.* 2016).

The questionnaire was distributed for completion to all respondents and completed questionnaires collected. The responses of pretesting revealed need to reword some of the questions which were not clear. A complaint raised by virtually all participants was that the questionnaire was a bit too long. While this was understandable, the researcher felt that removal of any question(s) would compromise the purpose of the study. The questionnaire was thus left as it was but purified making it more precise, accurate and reliable tool as exhibited by a Cronbach alpha of 0.7.

4.13 Administration of Questionnaire

Two research assistants were employed and each assigned several Provinces to service. Research assistant number one was assigned Manicaland; Midlands;

Mashonaland and Matebeleland Provinces. The second research assistant was assigned Harare. The researcher distributed the questionnaire in Masvingo and Bulawayo Province (BYO). A box of envelopes containing the questionnaire was delivered to each of the Department Heads, Human Resource Managers or Corporate Affairs Managers, as arranged, with delivery of the envelopes to the personnel in their respective offices left in the hands of these Senior Officers.

The empty boxes were sealed and left at the respective reception desks of the different Banks, wherein the respondents were required to place the completed questionnaire. The process required approximately four months to complete due to intermittent returns of the completed questionnaire, requiring several return visits by research assistants. Senior officers would be asked to remind respondents to kindly attend to the request. On completion of the field work, the returned questionnaires were kept in a safe (vault) at the offices of the researcher, with soft copies encrypted prior to analysis by the statistician.

4.14 Sample size

Of the 500 questionnaires distributed for the quantitative aspect, 406 were returned, representing a response rate of 81.2 percent, an average of 29 participants from each bank. Various authors posit that a response rate of at least 50 percent is deemed adequate for reviewing; with 60 percent regarded as good, and as very good when the response rate is 70 percent and above (Babbie 2004; Groves *et al.* 2009; Goraseb 2017). Since the study response rate exceeded 80 percent, it was deemed very good and thus accepted as an adequate representative sample size.

4.15 Data Analysis

Data analysis denotes validation and review of data gained from responses, with which to interpret or develop any theories (Remenyi & Bannister 2012). Key statistical techniques used in this study are summarised:

4.15.1 Quantitative Data Analysis

To enable quantitative data analysis, use was made of computer-based quantitative systems, namely, IBM SPSS Statistics v26, IBM SPSS Amos v26, and the PROCESS Macro for SPSS. The Process macro was used to cross validate the mediation tests

that had been done in Amos. The coding of questionnaire items into SPSS, allowed a template to be generated in the subsequent questionnaire response capturing. On completion, data were filtered, removing errors made in human capturing, along with missing items and outliers, followed by data analysis. The first system enabled addressing each of the research objectives through descriptive and inferential analysis, while the second system evaluated the indirect effects or the effects of mediation and moderation.

To ensure replicability as well as validity of the findings, robustness of the findings was tested. This was achieved through reverse causality tests, in addition to the endogeneity test, as prescribed (Hsiao 2007; Bell & Jones 2015; Leszczensky & Wolbring 2019). The Granger Causality Test was performed for the reverse causality test, while the Durbin-Wu-Hausman Test was carried out for the endogeneity test. All tests confirmed the study results as robust.

i Inferential Statistics

Hair *et al.* (2009) explain inferential statistics as drawing a conclusion on a population. Relationships and predictions were made and inferential statistics drawn, mainly to determine the significance of the study outcomes, to enable the feasibility of generalising to the total population (Field 2016). The inferential analyses used a 95 percent confidence level in all aspects as rejection threshold, this means a significance level of 0.05, as Field (2009) prescribed, as well as the SPSS default threshold (IBM 2016). All p-values were otherwise stated simply as *sig* in the SPSS output tables, at less than 0.05.

ii Descriptive Statistics

The researcher used descriptive statistics as aid to describe the data frequency distribution, central tendency measures (mean Scores), and dispersion measures (standard deviation, skewness, kurtosis). Furthermore, skewness and kurtosis are used to determine whether the data were normally distributed or not. Data scientists such as Field (2018) and Pallant (2016) are of the view that ranges of -1 to + 1 show that the data were normally distributed, and this gives justification to use parametric statistics such as Pearson's correlation, regression and SEM in AMOS.

The 5-point Likert scale median statistic was rated at 3.0, therefore, some degree of negativity is suggested by all mean values less than 3), whereas mean values greater than 3.0 implied a high level of respondent positivity (Field 2016). Furthermore, where standard deviation is concerned, the most desired is 0, which suggests the greatest degree of harmony in responses (Zikmund *et al.* 2012). Nonetheless, standard deviations between 0 and 1 are considered as most desirable, while deviations that are more than 2 are believed to be undesirable (Cooper & Schindler 2014; Zikmund *et al.* 2012).

iii Factor Analysis

The questionnaire was validated using factor analysis. The main purpose in the use of factor analysis was to determine a way of compressing or reducing data from a large set of variables into small components, without losing any information (Pallant 2007). Furthermore, correlations or similarities were established in the given data sets.

iv Confirmatory Factory Analysis (CFA)

CFA was done to validate constructs and achieved through convergent and discriminant validity, using IBM SPSS Amos v26. Following the guidelines of Chinomona, Dhurup and Chinomona (2013), factor loadings reported for items below 0.500, which is the minimum acceptable threshold, were deleted. CFA confirms validity of constructs prior to undertaking Structural Equation Modelling (SEM), which tested the research hypotheses.

v Structural Equation Modelling

SEM was also applied in the study, because it captures the relationships among the latent variables and highlights the relationship nature and magnitude that exists among constructs that are latent (Arslan, Yilmaz and Aksoy 2012). The constructs were assessed using fitness models such as Absolute Fitness as well as Incremental Fitness indices. According to McDonald and Ho (2012), determining how well the prior model fits the sample data is achieved through Absolute Fit Indices. Therefore, assessment of the measurement model's fitness was done by means of Goodness of Fix Indices (GFI), Chi-Squared Goodness of Fit test, and statistics that included its freedom value degree. Nevertheless, to complement the Chi-Square test use is made

of Incremental Fitness Indices (McDonald & Ho 2012). The acceptable thresholds of the fitness model indices of the Structural Equation Model are presented (Table 4.5), depicting specifications used in the evaluation and interpretation of the Structural Equation Model (Bagozzi & Yi 2012). The guidelines set out the levels considered acceptable, thus illustrating a correct relationship between the latent variables.

Table 4.5: Measurement and Structural Fit Indices

X ² /(df)	≤3.000
GFI	≥0.800
RMSEA	≤0.080
IFI	≥0.900
CFI	≥0.900

4.15.2 Qualitative Data Analysis

Qualitative data were produced in the field through interviews conducted by the researcher, wherein broader explanations were provided on all answers to the questions. Hatch (2002) defines qualitative data analysis as a process of arranging and interrogating (data) in a manner that allows users or researchers to observe a pattern, establish themes, develop an explanation or critiques, and determine relationships, as well as make comprehensive interpretations, and create theories more easily.

Interviews conducted were face-to-face and semi-structured, with a comprehensive interview guide that facilitated 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 be obtained with the quantitative questionnaire. All coding and analysis of participant responses was achieved through NVivo software (qualitative research software). According to Castleberry (2014), 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, hence allowing much needed time to discover tendencies, as well as recognising themes (Hilal & Alabri 2013).

4.16 Testing for Validity

Validity testing was undertaken, following data collection, which involved validating the research instrument to determine whether it measured what it was supposed to measure (Cohen, Manion & Morrison 2006; Gray 2009). Krishnaswamy *et al.* (2009) identified four methods of validity testing:

- i Content validity refers to the demonstrativeness of substance or material obtained by the research instrument. While the depth of the information gathered is important to the subject under study, the focus is on full representation of the questionnaire in seeking sufficient information.
- ii Face validity is regarded as the ability of a particular measure to conform to some common agreements on a given concept. Furthermore, it shows the substances that are expected to validate a model 'on the face of it', appear as if they can achieve the desired objective (measurement).
- iii Construct validity deals with a given concept and the extent to which the instrument or questionnaire can measure the constructs. The study ensured all relevant questions were skewed towards loan model effectiveness. Construct validity achieved by conducting convergent and discriminant validity. The latter is achieved by conducting using analysis of average variance extracted (AVE) of 0.5 and to determine convergent validity. Discriminant validity is determined by factor loading and Fornell-Lacker. Recently, a criterion called Heterotrait-Monotrait Ratio is suggested by Hair *et al.* (2017).
- iv Criterion validity testing denotes the accomplishment of and degree to which the questionnaire relates to other methods of data collection.

To test quantitative validity in this study, content validity was tested, wherein evaluation of the questionnaire was undertaken to confirm coverage of the subject matter and objectives. This was achieved through a pilot test. Variables considered of interest were measured considering their relevance, intrinsic value, representativeness and logic. Analytical input from experts and consultants in the field ensured the questionnaire would obtain adequate coverage, hence, it can be concluded that content validity was good.

Validity of qualitative data collection in this study was achieved through utilisation of purposive sampling, which facilitated selection of a sample that fully understood the study objectives or interest, as per the advice of Silverman (2001). In this work interviews were undertaken, with participants drawn from more than one commercial bank. The study obtained broader knowledge from a wide source, thus varying perspectives were brought for deliberation, while drawing participants from different members of various institutions strengthened this work, with investigation of the problem statement thus not undertaken from only one commercial bank and province (Bryman 2008).

4.17 Testing for reliability

The extent to which techniques of data collection will produce findings that are consistent is referred to as reliability (Babbie 2009). Different forms of reliability tests exist, including stability reliability, referred to as test-retest measures, showing the extent the data collection instrument is able to produce results that are constant at different times. Another reliability measure involves equivalence, which clarifies whether consistent outcomes are brought about by the measuring instrument across varied respondent groups. Another form of test is that of inter-rater reliability, which determines the magnitude of a measuring instrument producing consistent results once evaluated by several people (Gray 2009).

Composite reliability can be defined as the proportion of variance in an observed Score, accounted for by variance in the latent variable models, such as unambiguous reliability (Loehlin & Beaujean 2017). In addition, it measures the degree of observable variable measurement concerning latent variables, offering a robust reliability assessment by considering the contribution each latent factor brings to each item and its error. The range of the composite reliability values for the constructs is from 0.678 to 0.773; this largely satisfies the criterion of more than 0.6 that is recommended (Bagozzi & Yi 1988). The composite reliability test indicated reliability of the scales and constructs.

Internal consistency was also used to test reliability in this study. It deals with measuring instrument consistency, which is helpful in a repeat study. Furthermore, internal consistency validates the interconnectedness level of object measurement,

which measures a similar concept (Takakol & Dennick 2011) and can be achieved through two forms; these are Composite Reliability and Cronbach's Alpha Coefficient.

An alpha value that is 0.6 or higher suggests high internal consistency, however, an alpha value below 0.5 implies unreliable measurement items (Giddings 2006). In this work, the reliability analysis results show the range of the Cronbach Alpha Coefficient lies between 0.7 and 0.8 for the five objectives, suggesting some degree of internal consistency in each construct, which is detailed in the next chapter.

Reliability in using a qualitative method can be achieved by fully documenting and precisely laying down all procedures followed in a study (Franklin & Ballan 2001). Furthermore, these procedures are also considered an audit trail. In another version, Collingridge and Gantt (2008) opined that 'quality of results' as well 'consistency in quality' are regarded as reliability. Therefore, this work clearly spelled out the methodological approach applied and listed procedures followed to obtain the data, thus documenting everything that can be followed by any independent person. The study also identified those who participated, not by name, but by qualification and sector employed, demonstrating participant credibility. Moreover, after interviews, the researcher sought feedback on data, meaning or interpretations and conclusions from the participants, ensuring captioned responses were correct as evidence of credibility.

4.18 Model Development Methodology

The fifth research objective required that this study develops a suitable Loan Model which can be used by a commercial bank in Zimbabwe to evaluate corporate clients. Basel ii IRB Framework also encourages banking institutions to come up with their own internally developed credit risk models Basel ii (Basel Committee on Banking Supervision 2006). Herein is an outline of the method used in the development of the said model and the steps followed in the development are guided by Wooldridge (2013). The model is built based on a case study of a Zimbabwean Commercial bank which did provide the credit portfolio of corporates on their books by offering a credit register. The register did not show much details of a client except limit, exposure and status and whether performing or not performing. The observation of ethical code of conduct was fully regarded throughout the data collection period and analysis of the

collected data. To ensure confidentiality of client information, in this research this bank is called FM Bank.

4.19 Credit Data

The loan data comprised of 1 460 corporates of which 70 percent were considered good whilst 30 percent were considered bad. The method of awarding loans was the judgmental approach based on a risk indicator with 20 characteristics. For the reviewed period, the average loan tenure was 24 months. Loan data comprised of the corporate's profile and products, financial performance information and records reflecting repayment patterns of the customers. There exist several statistical model approaches or techniques adopted for credit risk assessment in literature. The most traditional ones include linear discriminant analysis (LDA) and LR. The latter has underpinned the development of this new model.

4.20 Regression Analysis Technique

Regression analysis comes with several variations but the most generic ones are linear regression and logistic regression (Wooldridge 2013). Regression analysis attempts to describe the relationship between a given variable, the regressand, with one or several other independent variables known as regressors. The general model specification for linear and LR models is given below:

$$y = X\beta + \varepsilon$$

Where: y is the continuous regressand of dimension $T \times 1$ where T is the total number of observations.

X is a $T \times k$ matrix of explanatory variables for k regressors.

β is a $k \times 1$ dimension of estimated coefficients, and

ε is a $T \times 1$ dimension of error terms.

This can be represented in matrix format as given below for $k=2$;

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} = \begin{bmatrix} 1 & x_{21} \\ 1 & x_{22} \\ \vdots & \vdots \\ 1 & x_{2T} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_T \end{bmatrix}$$

The multivariate linear regression model by Wooldridge (2013) is represented as follows.

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots \beta_k x_{kt} + \varepsilon_t$$

LR, which this study has employed, on the other hand, does not assume a linear function as the response term is bound between 0 and 1. It follows a sigmoidal/logistic function as depicted in Figure 4.2 below.

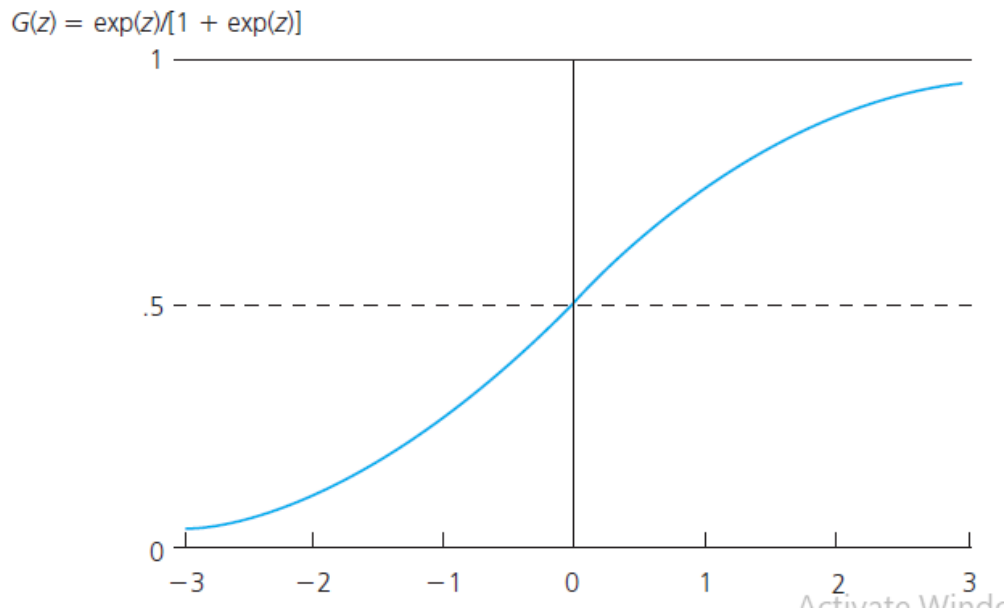


Figure 4.2: Logistic Function

Source: Kiruthika and Dilsha (2015)

The S-shape of the logistic function is explained by the following expression

$$F(z) = \frac{e^{z_i}}{1 + e^{z_i}} = \frac{1}{1 + e^{-z_i}}$$

Furthermore, Kiruthika and Dilsha (2015) provide a logistic definition of the LR model as given below;

$$\text{Logit}(p_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k$$

Where x_k is the k-th explanatory variable influencing p_i the conditional probability of default.

The model is so called due to the function F in fact being the cumulative logistic distribution, in order that it looks as shown below (Brooks 2008).

$$P_t = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_k x_{kt} + \varepsilon_t)}}$$

The main difference between Linear Regression and Logistic Regression models is that the outcome variable in LR is binary or dichotomous. This variation of logistic and linear regression is illustrated in both the parametric model choice and the assumptions. Once this difference is accounted for, the method used the same general principles as in linear regression, for an analysis using LR (Paddy 2012).

4.21 Steps in evaluating credit risk through Logistic Regression (LR)

Wooldridge (2013) highlights the following steps in developing a credit score model using LR technique.

4.21.1 Variable Selection

This process helps to reduce the risk of overfitting by reducing the number of independent variables (Wooldridge 2013). There is need to examine the pseudo- R² and accuracy of the classification result, the Akaike Information Criteria (AIC), Residual Deviance values and the Likelihood ratio chi- squared test. The indexes from these indicate that a variable with a lower index is preferred.

A summarised description (Table 4.6) of the data, including the coding criteria used, is illustrated below (Berger 2006; Abdou & Pointon 2011; Samreen *et al.* 2013).

Table 4.6: Model Variables

Variable	Description	Data Type	Coding Criteria
Default Status	Credit Risk Grade in terms of the internal ratings system based on historical performance	Categorical	0 – Defaulted 1 – Non-Default
Loan-Amt	The principal amount disbursed to the borrower	Numerical	N/A
Overdue	Total amount in outstanding instalments on other loans registered with Central Credit Registry Bureau	Numerical	N/A

Variable	Description	Data Type	Coding Criteria
Tenure	Length, in years, of the loan facility	Numerical	N/A
Interest-Rate	The price of the loan per annum	Numerical	N/A
Age of Corporate	The borrower's age in years as at the day of loan disbursement	Numerical	N/A
Monthly-Revenue/Income	Total revenue per month from reliable traceable sources	Numerical	N/A
External-Rating	Borrower's external credit history based on the Financial Clearing Bureau ratings.	Categorical	1. Good 2. Moderate 3. High / PEP
Security	Quality of security provided as collateral	Categorical	1. High Quality / Direct deductions 2. Moderate / Potentially under collateralised 3. High/ Potentially unsecured
Business Correlation with the Economy	Productivity of the business vis-à-vis the state of the economy	Categorical	1. Very low to almost negative 2. Low 3. Moderate 4. High 5. Very high to almost perfect
Management Quality	Competence and Capacity of Management in running the corporate	Categorical	1. Highly professional 2. Professional 3. Average 4. Visible lack of competence 5. Wide managerial skills gap
Running-Loans	Number of running loans as at the date of loan application	Numerical	N/A

Source: developed by author from Berger and Udell (2006) and Zaidi (2013) and field work

The variables selected were mostly recommendations from interviewees and some have been used by other scholars (Berger & Udell 2006; Zaidi 2013). Only those variables that have significant influence in predicting default have been selected in this model as are guided by the outcome of the LR technique.

4.21.2 Data Pre-processing

This stage involves the conversion of categorical variables into factor variables (Wooldridge 2013). It mainly involves the creation of dummies for qualitative data units and for categorical predictors, a total of $k+1$ dummies are created. At this stage, the data cleaning exercise is done, that is, when one has to deal with missing variables and units before fitting the model.

4.21.3 Data Partitioning

It is imperative to ensure that before fitting the LR credit score model, it has to be partitioned into the training and the testing set (Paddy 2012). For this study, the data was partitioned in a ratio of 70:30. This is to say that, 70 percent of it was the training set and 30 percent was the testing set.

4.21.4 Model Fitting

This is the stage where the data is imported into the estimation package and using the Maximum Likelihood (MLL) estimation procedure (Wooldridge (2013). The model is estimated to obtain the model coefficients and other important descriptive statistics. We carry out model and data tests on this stage until we get the best or final model.

4.21.5 Data tests and diagnosis

Various tests are conducted in this study to ensure that the data and the model is fit to produce reliable results.

4.21.6 Logistic Regression Data Tests

The LR model does not take any assumptions for normality, linearity or homogeneity and this makes it preferable, when compared to Discriminant Analysis (Wooldridge, 2013). The data tests for the LR model are meant to ensure reliability and validity of the results.

4.21.7 Multicollinearity

Multicollinearity occurs when two or more independent variables are highly correlated with one another in a regression model (Wooldridge 2013). It is detected where the standard errors carry values that are greater than 2.0 which indicates numerical

problems and therefore some of the independent variables that are highly correlated might need to be dropped.

4.21.8 Extreme Values

LR is also sensitive to outliers and extreme values. Therefore, series with extreme values have to be normalised so as to reduce the contribution of extreme values (Paddy 2012).

4.21.9 Goodness of Fit

The goodness of test was conducted under the following hypothesis:

H0: The model fits well of the data

H1: The model does not fit well on the data

4.21.10 Model Performance Evaluation

The performance of the model has been evaluated on the basis of several relevant methodologies with applications of such being focused on the testing set. To analyse the performance of the model, several tools and metrics were employed considering the possible class imbalance in the dataset.

4.21.11 Confusion Matrix

The Confusion Matrix also known as the classification matrix summarizes the correct and incorrect classifications that a classifier produced for a certain dataset. It measures the proportion of the correctly classified cases as good credit and as bad credit in a given data-set. The average correct classification rate is a significant criterion in evaluating the classification capability of the proposed scoring models (Abdou & Pointon 2011). Rows and columns of the confusion matrix must correspond to the predicted and true (actual) classes, respectively (Shmueli *et al.* 2017).

4.22 Study Limitations

Limitations are obstructions such as events as well as unforeseen shortcomings to the study process and outcomes and are beyond the control of the researcher (Berg & Latin 2004; Thomas, Nelson & Silverman 2011). Even though the research

assistants did a sterling job in distributing and collecting the questionnaire, the need remained for the researcher to travel the length and breadth of the target provinces to support the assistants and open doors of certain banks where challenges were encountered. This posed a huge financial constraint for the researcher.

4.23 Delimitations

Delimitations are restrictions enforced by the researcher, particularly in the scope of the study, that is, the nature of the study, geographical areas, as well as the duration of the study (Berg & Latin 2007; Thomas *et al.* 2011). Only employees of operational Commercial Banks and closed Commercial Banks were targeted for inclusion, which excluded employees of other financial intermediaries such as insurance firms. Furthermore, contributions from other lenders such as micro finance, pension funds such as NSSA, and lender of last resort - the RBZ, were not sought. The fact that the study was conducted within Zimbabwe only, caused a geographical delimitation as well.

4.24 Elimination of Bias

Bias, as described by Blythe (2005), is the unreliable stakeholder conclusion of a study, without much confidence in the results. This work eliminated bias by ensuring the entire target population was fully represented, using a sampling process that selected participants from different Commercial Banks with various backgrounds in lending, from all SA provinces, at different positions and work experience.

4.25 Ethical Considerations

Ethics denotes the morals, standards and principles related to what could be considered an appropriate way to obtain valuable information during a study (Mouton 2006; O'Leary 2014). These morals guide a study and ensure fair treatment of human beings without subjecting them to any harm or the potential for harm, be it mental or physical. Four aspects were identified as key ethical factors to consider in this study:

4.25.1 Ensuring participants give informed consent

Informed consent refers to the courtesy of advising participants about the nature of the study, possible implications and any intended recording for an interview, after which agreement to participate is obtained before data collection (Quinlan 2011). In

this study participants were furnished with all the necessary information, such as the overall objectives of the study and that there was no risk in participating, as their names and banks would not be required. The estimated completion time was given, established during the pilot study, as advised by David and Sutton (2011).

All this information was contained in a letter that accompanied the questionnaire, which was obtained from the University (Appendix 2c). This letter advised participants of the voluntary nature of participation, allowing anyone to freely withdraw, without penalty, at any stage in the research.

4.25.2 Ensuring voluntary participation

Voluntary participation refers to an informed decision made by a respondent to participate in a study after the research process is explained and being fully convinced of no privacy invasion and threats (Bryman & Bell 2007). In not giving participants any incentive or agreeing to payment in any form, on questionnaire or study completion. The complete questionnaire was provided to respondents e and not a section at a time, with full completion showing agreement to participate in the study. Interviews also took place at the most convenient time and place of the interviewee, demonstrating voluntary participation.

4.25.3 Ensuring no harm

Quinlan (2011) explained that harm refers to aspects that can be in physical format or anything with a detrimental effect on the participant after taking part in a study, such as self-esteem, stress, career prospects and/or development. Blanche, Durrheim and Painter (2006) emphasised safety of participants must be ensured, whether it is direct or indirect (mental or physical), as due to the research they would have participated in.

During the study no participant was wronged by the research during data collection. The harmlessness of the study was ranked to level two of the ethics standard set by DUT, indicating very low physical and mental harm, as well as risk to the participants, environment and animals. There was also no record of harm during data collection.

4.25.4 Ensuring confidentiality and anonymity

Confidentiality refers to when responses from study participants are not made publicly known, whereas anonymity signifies non-disclosure of participant identity during any part of or at any given time during the study (Wild & Diggines 2015). Assurance of confidentiality and anonymity in this study, neither participant names nor their office location were required in the questionnaire. Further to this, respondents' place of residence was not required, ensuring no tracking methods on the source of the response could take place.

4.25.5 Ensuring permission is obtained

Progress in many studies is impeded by of the inability to access not only the target population, but also the participants and organisation (Roper 2007), the need however exists to acquire information from the population best suited to the research and having access to participants that have the knowledge most relevant to the study.

To ensure this, permission to conduct the study was sought from the CEOs or bank representatives of all the registered Commercial Banks targeted for the study. Many Commercial Banks authorised distribution of the questionnaire and reduced it in writing (Appendices 4a to 4h). However, some of the Commercial Banks did not find it necessary to provide a permission letter, as it was not a bank specific case study and felt oral permission was sufficient.

4.26 Data Protection

Maree (2007) and Maree and Van der Westhuizen (2009) argued that whenever data are gathered and stored, there is a need to manage and protect privacy, making it necessary and imperative to ensure data storage is well-secured to mitigate access challenges by third party intruders. Furthermore, data is required to be protected from disasters and viruses, therefore, soft copies of the study questionnaire will be encrypted, while hard copies will be stored in a bank safe, locked 24 hours a day.

4.27 Data Retention and Destruction

There is need to keep data for a specific period for reference purposes, which can be achieved by depositing it in a well-secured repository which is with identity (ID) or password protection (Maree & Van der Westhuizen 2009; Pickard 2013).

Furthermore, data maintenance requires monitoring for essential changes in hardware and software used at the time of data collection, hence, any significant changes would call for an upgrade. Moreover, data retention can be successful by migrating data, copying or transferring the existing data onto better versions (software), supported by accurate records on changes made. Meanwhile, a consistent filing system must be maintained.

In addition, there is a need to simultaneously adhere to university policy and legislation on data management, related to regulatory and legal prescriptions on its disposal (Maree & Van der Westhuizen 2009; Pickard 2013). These policies will assist in ensuring data destruction is appropriate and securely undertaken, which guarantees that confidential information may not be accessed by unauthorised persons; this may be achieved by destroying hard copies through shredding or burning, while discs can be destroyed through soaking in acid to destroy the file. This work data shall be destroyed in line with college policy and guidelines and any encrypted files deleted.

4.28 Concluding summary

This chapter has given a detailed account of the research methodology followed in order to test the research objectives. Aspects such as research philosophy, were explained and justified. A mixed research methodology was applied, given its capacity to cover a large population as well as leverage of the two methods made it imperative. With the chapter having explained and justified the sampling procedure. An over view of the processes and quantitative tools used to measure the collected data was also presented in this chapter.

A detailed analysis and interpretation of the findings is set out in the next chapter.

CHAPTER FIVE

EMPIRICAL FINDINGS OF THE STUDY

5.1 Introduction

Research findings are presented in this chapter, starting with the quantitative phase results, obtained through a survey questionnaire, followed by qualitative phase results, accomplished through interviews. The objective of the study was to explore loan model effectiveness in commercial banks in a developing nation such as Zimbabwe, as a point of reference. The sub research questions that were answered by the study were (1) Which LPM Models are used in your bank to predict loan performance?; (2) Which parameter attributes do the commercial banks in Zimbabwe consider in LPM model development?; (3) How is the effectiveness of LPMMs and loan performance in Zimbabwean Commercial Banks analysed? ; (4) Does a loan model separate potential NPLs at evaluation stage? and finally, What influences a Commercial Bank to change its loan model or develop a model? For confidentiality reasons, the commercial banks under study are identified as operational banks and closed banks.

5.2 Quantitative Statistical Analysis

Data from the quantitative phase were obtained through a questionnaire, with a total of 406 responses received, which made up the study sample. The data were captured and analysed on SPSS Version 26, as well as on IBM SPSS Amos v26, which yielded the inferential and descriptive results discussed hereunder. To establish the statistical model with which to explain the relationship between the variables, SEM was performed. Following this, to determine their impact on one another, the hypotheses were tested between model constructs.

5.3 Results

These results are presented in line with the questionnaire.

5.3.1 Demographic Information

i. Gender

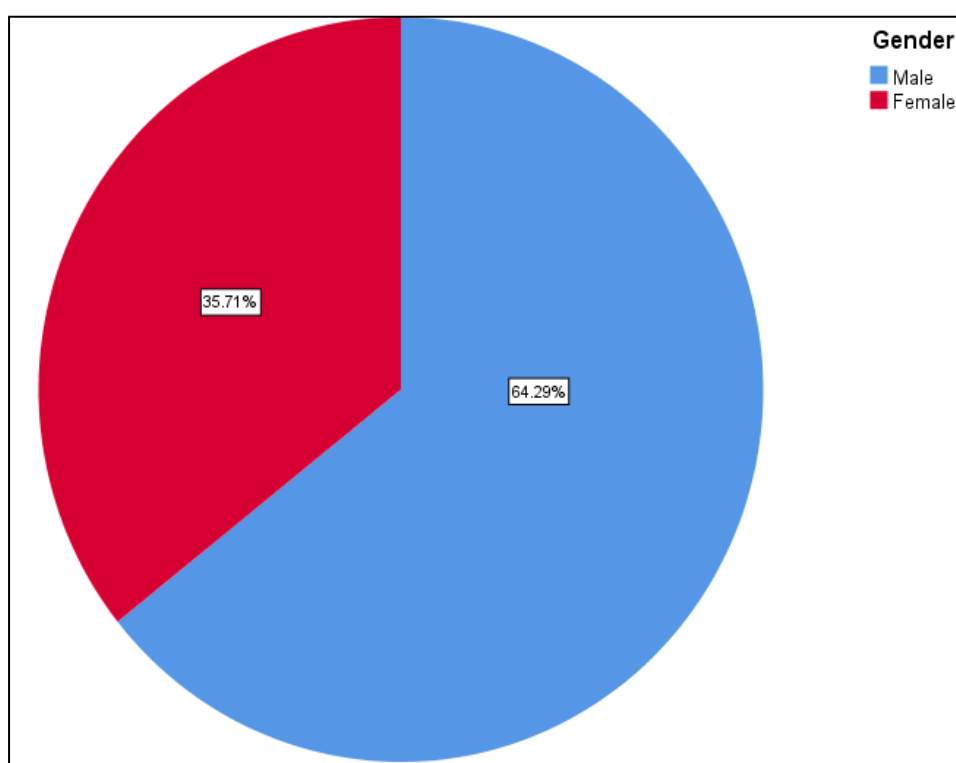


Figure 5.1: Gender of respondents

The results (Figure 5.1) reveal there were more men than women employees at the targeted levels among the Commercial Banks in Zimbabwe. Whilst the gender of the officials has no bearing on the aim of the study, it is interesting to note the country's patriarchy prevails in the Banks as well. This is confirmed by the observation made in a survey by the Zimbabwe Labour Force (2014), which showed banks as part of some sectors where women are least employed. This finding also resonates with the ZIMSTAT (2016) report that males dominate within the banking sector and accounted for almost 60 percent of banking employees. The ratio of participation, however, does not have any negative influence on the findings because the focus of this study is not gender sensitive.

ii. Educational Level of Respondents

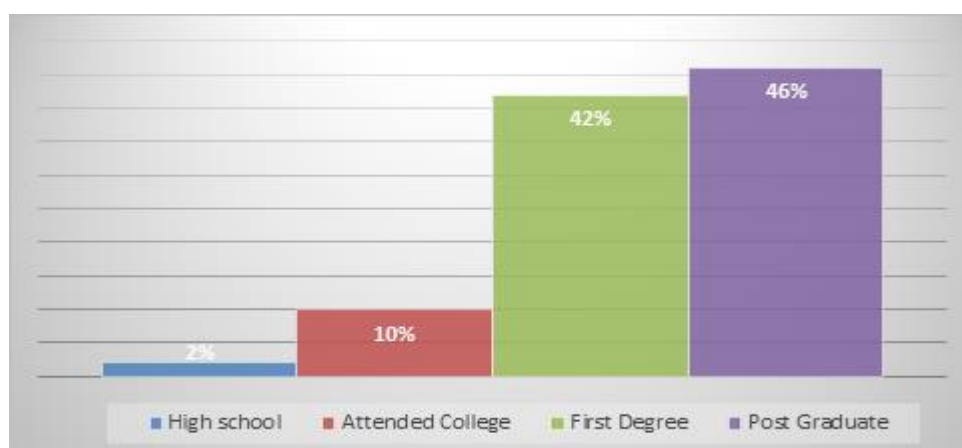


Figure 5.2: Educational Level

The result (Figure 5.2) reflects that the majority of the respondents were literate, and thus able to understand the questions. The findings are consistent with the UNDP (2010) that observed Zimbabwe had the highest literacy rate in Africa. This observation has also been confirmed by Garikai and Mlambo (2016), while ZIMSTATS (2019) puts the literacy rate in Zimbabwe at 97 percent at the time.

iii Experience in the sector

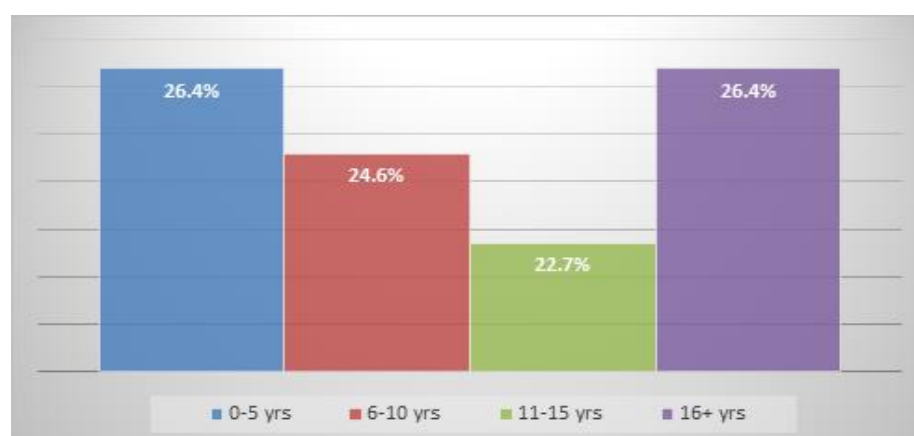


Figure 5.3: Work Experience

The results (Figure 5.3) show employees in the banks possessed acceptable levels of work experience. Thus, given their institutional memory and input into productivity creates a high probability of reinforcement of loan evaluation, because they have a

background in the banking sector, as well as the particular bank and industry loan performance. Roy, Acharya and Roy (2016) postulated that having most of the respondents with a high level of experience improves reliability of the study results. Therefore, the contribution by bankers to the study can be said to be of great value due to the practical experience of participants.

iv Designation of Respondents

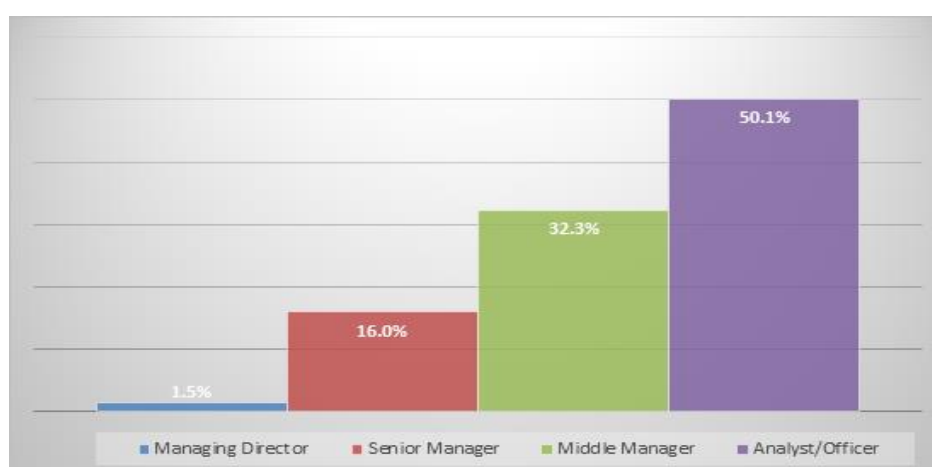


Figure 5.4: Designation of respondents

The results (Figure 5.4) reveal that all levels in the lending departments participated in the study, with Analysts being in the majority. This is admirable because analysts are indeed specialists in the loan evaluation process and are at the coalface of operations. This level of balance, according to Jaggia and Kelly (2013) and Coolican (2014), ensures concerns and observations from all levels in the lending structure hierarchy are captured, which eliminates potential bias that could have resulted, had only management views been considered.

5.4 Existence and application of Loan Portfolio management models

The following results relate to questions aimed to test the first research objective of this study, which sought to establish whether LPMs existed and were applied.

Table 5.1: The bank uses the Internal Credit Score model

		Frequency	Valid Percent
Valid	Strongly agree	155	39
	Agree	201	50
	Neutral	28	7
	Disagree	18	4
	Strongly disagree	1	0
	Total	403	100
Missing	System	3	
Total		406	

It was found (Table 5.1) that as much as 89 percent of the participants agreed the Credit Score model was being used by Commercial Banks in Zimbabwe. By using this model, they can quantify credit risk at the outset of loan evaluation and the ability to separate potential good and bad accounts makes it applicable. Durand (1941) and DeYoung (2008) expressed their satisfaction with the usefulness of the model. Some of its benefits are that shareholders' funds are safeguarded by only granting loans to clients with potential to fulfil their obligations. Furthermore, retention of creditworthy customers is improved due to the quick turnaround time facilitated by the model. The Credit Score model mitigates bias that would result from judgement decisions by lenders.

Table 5.2: The bank uses the Z-Score model

		Frequency	Valid Percent
Valid	Strongly agree	12	3
	Agree	64	16
	Neutral	103	26
	Disagree	205	50
	Strongly disagree	19	5
	Total	403	
Missing	System	3	
Total		406	

The result (Table 5.2) shows the Z-score model was not widely used by most banks, as indicated by 81 percent of the participants, who mostly did not concur with the statement or were uncertain. This result strongly suggests the banks find this model

to be incompatible with their needs. Yet, Dondo (2019) argues it can be applied in Zimbabwe to predict risk of failures of construction companies. The findings are in contrast with the model's popularity in the USA, where it has successfully predicted distressed businesses and bankruptcy in companies (Hayes, Hodge & Hughes 2010; Johansson & Kumbaros 2011). As things stand, it does not appear suitable for Zimbabwean conditions.

Table 5.3: The bank uses the Asset-Based model

		Frequency	Valid Percent
Valid	Strongly agree	24	6
	Agree	235	58
	Neutral	118	29
	Disagree	22	6
	Strongly disagree	3	1
	Total	402	
Missing	System	4	
Total		406	

This result (Table 5.3) shows 64 percent of participants favoured the Asset-Based model, suggesting it was considered second best in popularity among Commercial Banks in Zimbabwe, following the Internal Credit score. Nyangara (2013) determined that although the model exists in Zimbabwe, it does not become helpful or applicable in the absence of suitable security from clients such as SMEs. Whilst its popularity may appear moderate in Zimbabwe, Fatoki (2014) and Ollows and Moro (2015) found the model generally utilised by banks in other parts of Africa, with mandatory security. The Asset-Based model is, therefore, security sensitive.

Table 5.4: The bank uses various models on different loan products

		Frequency	Valid Percent
Valid	Strongly agree	41	10
	Agree	151	37
	Not sure	113	28
	Disagree	83	21
	Strongly disagree	15	4
	Total	402	100
Missing	System	4	
Total		406	

The findings (Table 5.4) illustrate that as much as 53 percent of the respondents were either unsure or disagreed that the banks use different models for different products. There can be various reasons for such a response. For example, it is quite possible an Internal Credit Score model can be tailor-made for all bank loan products, with a difference only on the cut-off Score. It is noteworthy that as many as 47 percent of the respondents confirmed the banks employed various models for different products. For instance, the Z-Score can predict bankruptcy over a three-year period, whilst some Internal Credit Score models are only designed specifically for personal loans. A wide range of models also demonstrates their applicability in a particular institution.

The results resonate with Berger and Udell (2006), who postulate that one model, such as the Credit Score, can evaluate an individual (personal loan) as well as a company (corporate loan) over a 12-month period, whilst the Z-Score model can predict bankruptcy up to three years. Therefore, what determines model choice is the product type and its outlook, which incorporates issues such as tenure. Companies that require medium- and long-term loans of between five and ten years will need a model with the capacity to focus on the long-term.

Table 5.5: A Loan Portfolio Management Model is a Score sheet used in analysing creditworthiness of a borrower

		Frequency	Valid Percent
Valid	Strongly agree	42	10
	Agree	204	51
	Neutral	40	10
	Disagree	114	28
	Strongly disagree	2	1
	Total	402	100
Missing	System	4	
Total		406	

The results (Table 5.5) show a large percentage of participants (80 percent) agreed that a LPMM was in the form of a Score sheet and used by the bank to record Scores obtained by the borrower on items pertinent to the application at hand. Participants agreed a Score sheet gave consistency and made their evaluation systematic. The majority of the respondents also confirmed they knew the Score sheet; which is a product of the work developed by Durand (1941), who proposed variables should be weighed through scores. The findings corroborate research by Lee and Chen (2005) and DeYoung *et al.* (2008), who concurred that a model used for evaluating personal loans, credit cards and small loans is in the form of a Score sheet. Chen *et al.* (2009) also emphasised the need to have a Score sheet when they conducted a study in the USA.

Table 5.6: A Loan Portfolio Management Model is a ratio used in analysing creditworthiness of a borrower

		Frequency	Valid Percent
Valid	Strongly agree	30	8
	Agree	121	30
	Neutral	47	12
	Disagree	173	43
	Strongly disagree	29	7
	Total	400	100
Missing	System	6	
Total		406	

The result (Table 5.6) reveals that a high percentage of respondents (62 percent) do not support the issue of ratios, contrary to their prior agreement on the Internal Credit Score as the most widely used model, which uses ratios as variables. A model is built on various factors and a ratio is one of the components that may be weighed to compute a final Score of the model. Megginson *et al.* (2008) define a ratio as a value of compared figures on financial statements of an applicant. A model such as a Credit Score is defined by Anderson (2007) as the transformation of relevant data into numerical measures that guide credit decisions, by using statistical techniques.

Saleh *et al.* (2017) and Al-Manaseer and Al-Oshaibat (2018) are convinced ratios are beneficial in guiding credit decisions, as they: simplify the interpretation of financial statements; help in trend analysis which involves comparing a single company over a period; help users of financial statements to easily judge a company financial position by just looking at few numbers instead; and the presence of high probability of accurately determining future trends of company financial performance, on the basis of current financial position or based on ratio outlook, which is very influential in the loan model for lending decisions.

Table 5.7: A Loan Portfolio Management Model uses a multivariate method in analysing creditworthiness of an applicant

		Frequency	Valid Percent
Valid	Strongly agree	139	35
	Agree	202	50
	Neutral	41	10
	Disagree	16	4
	Strongly disagree	3	1
	Total		
Missing	System		
Total		406	

The findings (Table 5.7) confirm that 85 percent of the participants are familiar with a multivariate method, which resonates with Altman (1968), whose Z-score model has five variables, making it a multivariate formula, and that these variables are used to analyse bankable projects. This is helpful, because where a single variable has weaknesses, the other ones help in leveraging it to make a stronger prediction. Gritta

et al. (2008), Rao *et al.* (2013), and Hsu (2017) agreed the method is relatively easy to calculate and the data required for the equation can easily be found from a company's financial reports, allowing bankruptcy prediction to be attained. However, a major shortcoming of the model in applying this formula is that one element, namely the market value of a company, may not be obtained on non-listed companies.

Table 5.8: The bank measures model accuracy by comparing the number of defaults to performing loans

		Frequency	Valid Percent
Valid	Strongly agree	251	62
	Agree	93	23
	Not sure	38	9
	Disagree	20	5
	Strongly disagree	3	1
	Total	405	100
Missing	System	1	
Total		406	

The result (Table 5.8) shows that 85 percent or more of participants agreed banks do measure efficiency on viewing defaults and relating them to loans. This implies measuring of model accuracy is imperative, as it demonstrates its continuous applicability on loan evaluation to the user. The findings are in line with Lieli and White (2010), Samreen and Zaidi (2012) and Rao *et al.* (2013), who maintain accuracy of a model is achieved after relating or differentiating outstanding debtors to debtors servicing their obligations. The positive outcome indicates the model is performing adequately.

Table 5.9: The bank measures model accuracy by comparing Type i and Type ii errors

		Frequency	Valid Percent
Valid	Strongly agree	32	8
	Agree	109	27
	Neutral	200	50
	Disagree	54	14
	Strongly disagree	4	1
	Total	399	100
Missing	System	7	
Total		406	

The results (Table 5.9) reflect that 65 percent of the participants were not convinced the banks use Type i and Type ii errors as a measure of loan model efficiency. Schweser (2013) defined a Type i error as that which makes a bad client look creditworthy, while a Type ii error is that which makes a good applicant appear bad. These types of errors result in loss of potential quality loans. The findings conflict with Samreen and Zaidi (2012) and Samreen *et al.* (2013), who found model accuracy is demonstrated by the lowest error rate, among other factors.

Table 5.10: The bank measures model accuracy by using non-performing ratios

		Frequency	Valid Percent
Valid	Strongly agree	139	35
	Agree	210	52
	Neutral	43	11
	Disagree	10	2
	Strongly disagree	1	0
	Total	403	100
Missing	System	3	
Total		406	

The result (Table 5.10) shows a high number of participants (87 percent) agreed with the statement that Banks use non-performing ratios to measure model efficiency. A non-performing ratio is an indicator of the level of loans with instalments that have not been serviced for a period exceeding 90 days (Grieser & Wulfken 2009). The results are consistent with Rezac and Rezac (2011), as well as Pradhan (2014), who

confirmed the level of NPLs is an indication of model accuracy. This makes it imperative for the bank to apply a model that brings in best results.

Table 5.11: Low facility management costs demonstrate model accuracy

		Frequency	Valid Percent
Valid	Strongly agree	13	3
	Agree	101	25
	Neutral	211	52
	Disagree	71	18
	Strongly disagree	7	2
	Total	403	100
Missing	System	3	
Total		406	

The results (Table 5.11) show 52 percent of participants; which is a considerable number, do not subscribe to the statement, indicating banks do not use this method as a measure of model accuracy. Facility management costs are fees levied for the maintenance of an existing loan (Berger 2006). The findings are also in line with Miller's (2009) observation that model efficiency is determined by the accuracy ratio. Additionally, Gezu (2014) stated the best measure of model efficiency is shown by low NPLs and not low facility management.

Table 5.12: Turnaround time of a bank is viewed as a model's accuracy

		Frequency	Valid Percent
Valid	Strongly agree	21	5
	Agree	146	36
	Neutral	140	35
	Disagree	93	23
	Strongly disagree	5	1
	Total	405	100
Missing	System	1	
Total		406	

The results (Table 5.12) reveal that the majority (59 percent) of the participants disagreed or were uncertain about using time frames as a measure of efficiency. Only a few of the participants agreed time could be used as a measure of efficiency,

suggesting model applicability might be influenced by time. Turnaround time, according to Siddiqi (2017), refers to how long it takes for a bank to process a loan application using a model to analyse data feed into its system. TransUnion (2007) and Siddiqi (2017) agree with the minority that a bank can measure efficiency using turnaround time, as it facilitates quick decision-making.

5.5 Model Parameter Attributes

The following results relate to questions that aimed to test the second objective.

Table 5.13: The Bank uses industry-based parameters

		Frequency	Valid Percent
Valid	Strongly agree	51	13
	Agree	271	67
	Neutral	70	17
	Disagree	7	2
	Strongly disagree	5	1
	Total	404	100
Missing	System	2	
Total		406	

It is shown (Table 5.13) that a high percentage of the respondents (80 percent) viewed industry parameters as fundamental to this objective. The industry parameters referred to here are Scores, scales and/ or acceptable ratio levels, such as debt to income ratio on personal loans. These are set by the regulator to ensure the loan model achieves its objective of successfully separating potential bad accounts from good accounts. The finding confirms that banks in Zimbabwe are compliant with regulator policies. Singh and Dutta (2014) also found the Reserve Bank of India sets parameters, which are used in the financial sector in India.

Table 5.14: Past loan performance experienced by a bank is considered when setting parameters

		Frequency	Valid Percent
Valid	Strongly agree	56	14
	Agree	292	72
	Neutral	41	10
	Disagree	13	3
	Strongly disagree	2	1
	Total	404	100
Missing	System	2	
Total		406	

The result (Table 5.14) shows that the overwhelming majority (86 percent) of respondents agreed past loan performance experienced by banks was considered when setting parameters. It means banks first examine past trends of loan performance and decide whether the previously used parameters were of great influence in predicting performing loans. Credit history is, therefore, important and can help in deciding an additional attribute. Basel ii (Basel Committee on Banking Supervision 2006) has endorsed the importance of these parameters, stating these should be continually evaluated and reviewed.

Table 5.15: Parameters initiated by bank or by consultant

		Frequency	Valid Percent
Valid	Strongly agree	33	8
	Agree	180	45
	Neutral	130	32
	Disagree	58	15
	Strongly disagree	0	0
	Total	401	100
Missing	System	5	
Total		406	

The results (Table 5.15) show that, in total, 53 percent of the participants alluded that the banks or the model developers are empowered to craft the parameters in line with the loan product and target client. They simply have to ensure these meet

regulator and international guidelines or standards. All parameters have some attributes linked to them to make the model sound.

This corresponds with research by Durand (1941), who posited that parameters were not adopted from any theory or market but initiated by the developers or banks, as they are familiar with potential risks that need to be mitigated. According to Rosch and Scheule (2007), Basel ii guidelines permit banks to create parameters in their lending models to suit their credit culture.

Table 5.16: The model can incorporate sizeable factors such as financial and behavioural characteristics

		Frequency	Valid Percent
Valid	Strongly agree	27	7
	Agree	284	71
	Neutral	84	21
	Disagree	4	1
	Strongly disagree	1	0
	Total	400	100
Missing	System	6	
Total		406	

The result (Table 5.16) illustrates a high number of positive responses (78 percent) from the participants, which indicates the importance of including many factors in a model. Financial factors in a model relate to issues such as income and other financial obligations. Behavioural aspects relate to reports on the conduct of the borrower from previous lenders, as well as clearing bureau reports.

The findings resonate with Leshno and Spector (1996) who applied 41 variables, whilst Mačerinskienė and Ivaškevičiūtė (2008) also emphasised the need for a sizeable number of factors in the model that may impact its efficiency. This further suggests no credit fact should be discarded when developing variables that analyse risk of a borrower.

Table 5.17: Outcome probabilities of a model are pre-defined

		Frequency	Valid Percent
Valid	Strongly agree	35	9
	Agree	249	62
	Neutral	76	19
	Disagree	40	10
	Strongly disagree	1	0
	Total	401	100
Missing	System	5	
Total		406	

The results (Table 5.17) show that in total, 71 percent or the majority of participants validated the statement because the outcome reveals the model results. These include that minimum Scores are set in advance to express the level of risk, along with consequences expected thereafter. This means the banks do loan evaluation as guided by a Score sheet that shows pass or fail, which translates to the approval or decline of a loan applicant. A combination of parameter attributes is used to build a Score to determine potential good and bad clients.

Altman (1968) already set the outcome probabilities when developing the Z-score, that when the final score of a borrower is 1.81 points, this would be a grey area, whilst 2.67 would be the minimum pass threshold.

Table 5.18: Model output can be ranked

		Frequency	Valid Percent
Valid	Strongly agree	68	17
	Agree	285	71
	Neutral	37	9
	Disagree	11	3
	Strongly disagree	0	0
	Total	401	100
Missing	System	5	
Total		406	

The result (Table 5.18) reveals that 88 percent of participants agreed with the statement that output of a model can be ranked. To rank an output means placing

results in an order that displays how a client has scored in certain categories. This reveals the strengths and weaknesses of the applicant. The bank will use this to determine the credit limit or the amount of security needed. It then ultimately gives the final score, showing whether he or she is bankrupt (1.81) or passes the evaluation (2.67), with 2.99 being the best score. The responses agreed with Pavan and Todeschini (2008), who stressed the need for ranking model outcome as it facilitates client classification to differentiate between anchor clients and average customers.

Table 5.19: The model benchmark is well-defined

		Frequency	Valid Percent
Valid	Strongly agree	45	11
	Agree	157	39
	Neutral	76	19
	Disagree	115	29
	Strongly disagree	7	2
	Total	400	100
Missing	System	6	
Total		406	

The result (Table 5.19) shows 50/50 responses of participants, which means there are mixed views as to whether the model benchmark is well-defined. Defining a model benchmark means parameters and variables that determine the final score can be traced and are well-structured. There could also be many assumptions in generating Scores, as well as parameters, which would make it difficult for the bank to have a reference point. Halle and Goldberg (2010) agree it is sometimes difficult to define a benchmark. Abdou and Pointon (2011) also concur and emphasise that cut-off point is not standard and complicates predefining the model score.

Table 5.20: The model is robust and not reviewed/replaced often

		Frequency	Valid Percent
Valid	Strongly agree	42	10
	Agree	202	50
	Neutral	70	17
	Disagree	84	22
	Strongly disagree	4	1
	Total	402	100
Missing	System	4	
Total		406	

The result (Table 5.20) shows that the majority (60 percent) of participants were satisfied that current loan models were considered strong and not replaced or reviewed often. They are happy with the parameters and variables applied and that these have a substantial influence on loan evaluation.

The results augment a study by Blochlinger and Leippold (2006), who found that a superior or robust model mitigates adverse selection and the bank then only lends to low-risk clients with a low probability of defaulting. There is thus no need to replace the model. Samreen and Zaidi (2012) similarly noted that the Credit Score model achieved 100 percent accuracy, demonstrating its robustness and thereby implying no need to look for another alternative tool for loan evaluation. Therefore, there is no need for an institution to replace a model that can optimise a performing loan book.

5.6 Effectiveness of Loan Portfolio Management Models

Below are results pertaining to the third objective of this study.

Table 5.21: A model is used to identify good clients

		Frequency	Valid Percent
Valid	Strongly agree	92	23
	Agree	248	61
	Neutral	42	10
	Disagree	20	5
	Strongly disagree	3	1
	Total	405	100
Missing	System	1	
Total		406	

The results (Table 5.21) reflect that 84 percent of participants regarded a model as a tool used to identify good clients. A model is applied to transform relevant data into measurable Scores that reveal the likelihood of an applicant to have capacity to pay in a set period, or not. Going by that result, the lender will consider only those clients who would have shown capacity to pay by meeting a certain Score line. The effect of a model should, therefore, be demonstrated by loan performance following its selection criteria.

The result corroborates assertions by Gup and Kolari (2005), Anderson (2007) and Miller (2009) determined that loan models facilitate informed decisions on accepting or declining loan applications. In other words, this tool can ascertain and classify good clients and bad clients.

Table 5.22: A model ensures security adequacy

		Frequency	Valid Percent
Valid	Strongly agree	78	19
	Agree	224	55
	Neutral	41	10
	Disagree	58	14
	Strongly disagree	3	1
	Total	404	100
Missing	System	2	
Total		406	

The result (Table 5.22) shows agreement was indicated by 74 percent of the respondents that it is a model which enables a bank to obtain adequate security; that

the model Scores guide the lender on the security cover amount expected for a granted loan. Credit policy on security aspects may also be fulfilled on the back of loan model results. Additionally, security cover also reveals the effectiveness of a model because without a model Score, the bank may not know the extent of their exposure.

The results validate Japhet and Memba (2015), who opined that adequate security is a result of model outcome when extending an advance to borrowers, whilst Siddiqi (2017) stated the Credit Score model sets security. The final Score obtained thus guides the lender on both amounts to be granted, as well as security cover.

Table 5.23: A model determines regular review of security

		Frequency	Valid Percent
Valid	Strongly agree	27	7
	Agree	154	39
	Neutral	149	38
	Disagree	61	16
	Strongly disagree	1	0
	Total	392	100
Missing	System	14	
Total		406	

This result (Table 5.23) demonstrates that 54 percent of participants were either uncertain or disagreed with the notion that a model serves a purpose in security review. This suggests the main role of a loan model is to distinguish between bankable projects and unbankable projects, based on merit. However, 46 percent of respondents indicated that risk levels shown by a model should be addressed by reviewing security.

The minority view resonates with that of Sarlija, Bensic, and Bohacek (2004), who highlighted judgemental techniques, which do not use scores, can fully determine risk levels. Gaps that need to be covered by security whenever security reviews are undertaken can thus not be determined. In a different view, Berger, Frame and Ioannidou (2011) confirmed that any exposure gap identified by a model necessitates additional security during the monitoring period of a facility. Additionally, Siddiqi

(2017) asserted that models consistently assess risk, therefore, there is a positive relationship between loan risk premiums and collateral pledges. The conclusion is that there is a mixed view on effectiveness of a loan model towards security review.

Table 5.24: A model guides on measures to be taken when a loan is in doubt

		Frequency	Valid Percent
Valid	Strongly agree	27	7
	Agree	152	37
	Neutral	154	38
	Disagree	68	17
	Strongly disagree	4	1
	Total	405	100
Missing	System	1	
Total		406	

The result (Table 5.24) shows as many as 44 percent of participants indicated model outcome does not influence appropriate action taken by a bank when there are signs of doubt, in fact, a possibility of failure to perform. A minority view (18 percent) is that the outcome recorded during a loan evaluation by a loan model provides the basis on which the bank may make an appropriate action to protect itself from NPLs. For example, should a borrower achieve Scores below the benchmark set by a particular bank, the application will be declined or the amount granted reduced. The guide from a model makes the tool handy and effective in NPL mitigation.

This minority view concurs with Anderson (2007) and Thomas *et al.* (2017), who maintained that the level of risk or probability that a client will default displayed by the model enables the bank to act appropriately, which mitigates NPLs. The bank needs to be proactive in ensuring high exposure to risk is mitigated.

Table 5.25: A model guides the assessment of sister companies of a borrowing corporate client

		Frequency	Valid Percent
Valid	Strongly agree	27	7
	Agree	142	35
	Neutral	130	44
	Disagree	51	13
	Strongly disagree	27	1
	Total	401	100
Missing	System	5	
Total		406	

In this result (Table 5.25), 58 percent of the participants were uncertain and disagreed that a model is a tool used to assess subsidiaries of a company. This implies the model may not be able to evaluate creditworthiness of certain companies in a group. 42 percent of the participants agreed with the statement, meaning the loan model does not differentiate its analysis based on evaluating a subsidiary company. Therefore, it can be used on any company. The bankability of sister companies in the same holding company may be evaluated separately, using the same model to determine each entity's financial health, because they provide different information that is weighed accordingly. It is imperative to determine effectiveness of a model across all companies as there may be leverages.

The findings conflict with Durand (1941), who applied his model to any borrowing client, whilst Altman (1968) targeted manufacturing concerns listed on the stock exchange, notwithstanding relationships with other sister companies. There was also no discrimination from Orgler's (1970) Asset-Based model, which is only largely based on security of the borrower as source of repayment and not concerned with existing relationships of companies. This suggests these models can be applied even on sister companies.

Table 5.26: A model is used to predict bankruptcy

		Frequency	Valid Percent
Valid	Strongly agree	31	8
	Agree	257	64
	Neutral	45	11
	Disagree	67	17
	Strongly disagree	2	0
	Total	402	100
Missing	System	4	
Total		406	

The result (Table 5.26) shows the majority or 72 percent of respondents were of the opinion all the models under study are portrayed as able to predict bankruptcy. This was based on their practical experience. For example, the Z-score is said to be good at predicting a three-year term.

As explained by Liang, Tsai and Wu (2015), as well as Altman (2018), bankruptcy prediction by a model is considered critical in the lending process. This will assist the bank in making an informed decision to either continue with the transaction knowing the possible consequences or completely declining it. However, precautionary measures may be considered, such as requesting more security as a fall-back position.

Table 5.27: A model determines Non-Performing Loans

		Frequency	Valid Percent
Valid	Strongly agree	48	12
	Agree	226	56
	Neutral	72	18
	Disagree	54	13
	Strongly disagree	2	1
	Total	402	100
Missing	System	4	
Total		406	

The results (Table 5.27) indicate that combined, more than half or 68 percent of participants contended that NPLs are detected at evaluation stage, where the model

gives the borrower a low score. There is a view that a client may pass loan evaluation stage but circumstances later change, meaning the model would have been unable to predict that. However, the bank uses available information at the time of evaluation, trusting the model to successfully detect NPLs.

The findings are inclined to observations made by Anderson (2007) and Swamy (2015) that non-quality assets are determined by models. Accordingly, any client displaying high credit risk characteristics is not approved for funding because there is evidence of a high probability of failing to service debt in the near future.

Table 5.28: The level of performing loans is compared to the total loan book

		Frequency	Valid Percent
Valid	Strongly agree	115	29
	Agree	246	61
	Neutral	28	7
	Disagree	10	2
	Strongly disagree	5	1
	Total	404	100
Missing	System	2	
Total		406	

The result (Table 5.28) shows almost all participants (90 percent) agreed assets held are compared; those performing against the entire book to ascertain the model's effectiveness. Thus, establishing the extent of the loan model impacts loan performance. The total loan book refers to all loans granted by the bank, whether good or bad.

These findings are in line with Samreen and Zaidi (2012) and Siddiqi (2017), who highlighted that when bank performing loans are compared to the entire loan book, the results show the effect of the model. In addition, the model should lower costs or losses and be efficient in suggesting that, when the level of performing loans is large compared to NPLs, it can be concluded the model is useful.

Table 5.29: Non-performing loans are caused by poor planning

		Frequency	Valid Percent
Valid	Strongly agree	73	18
	Agree	247	61
	Neutral	66	16
	Disagree	16	4
	Strongly disagree	3	1
	Total	405	100
Missing	System	1	
Total		406	

The results (Table 5.29) display that the majority of participants (79 percent) viewed poor planning as a cause of NPLs. Planning referred to here is that of a borrower and NPLs are those that default within 90 days. A borrower is expected to arrange with suppliers on quantities and quality of inputs and logistics, which will not upset production plans, because failure to produce on time leads to no sales or income to service the debt.

Results resonate with views by Muchomba (2016) that management planning, financial planning and marketing planning have a positive relationship with loan repayment. Therefore, any poor planning is likely to derail trade receipts, impacting loan repayment prospects. Nonetheless, Mabvure *et al.* (2012) found other circumstances in Zimbabwe resulted in NPLs, such as the integrity of clients, natural disasters and government policies.

Table 5.30: Non-performing loans are a result of poor markets

		Frequency	Valid Percent
Valid	Strongly agree	98	24
	Agree	267	66
	Neutral	29	7
	Disagree	11	3
	Strongly disagree	0	0
	Total	405	100
Missing	System	1	
Total		406	

The results (Table 5.30) point out that poor markets influence NPLs, demonstrated by 90 percent of participants that agreed with the notion. This suggests market vagaries can upset trade receipts, despite the project having been bankable at inception. This means it is important for the borrower to retain market share by being competitive. Consequently, better sales will enable it to service its debt. A need therefore exists to weigh company market to determine model effectiveness.

Trade receipts are indeed negatively impacted by low markets (Waweru & Kalani 2009; Richard 2011), with borrowers consequently incapacitated in the absence of cashflows and unable to service the debt.

Table 5.31: Non-performing loans are caused by poor cash flows

		Frequency	Valid Percent
Valid	Strongly agree	88	22
	Agree	267	66
	Neutral	39	10
	Disagree	10	2
	Strongly disagree	0	0
	Total	401	100
Missing	System	5	
Total		406	

The result (Table 5.31) shows this statement was overwhelmingly supported by the respondents (88 percent). Poor cash flows could be due to constraints in business operations, including finance charges, political and social issues or depressed markets, which impact cash flow generation. An effective model should be able to analyse and score future cash flows.

Bessis (2010) emphasised the impact of negative cash flows as leading to delay in receiving borrowers' payments, while Waweru and Kalani (2009) felt NPLs are due to legal issues that delay the settlement of commercial disputes, absence of security as a fall-back position and inadequate lending personnel skills.

Table 5.32: Non-performing loans are caused by use of an outdated model

		Frequency	Valid Percent
Valid	Strongly agree	70	17
	Agree	248	61
	Neutral	61	15
	Disagree	21	5
	Strongly disagree	1	0
	Total	401	100
Missing	System	5	
Total		406	

The results (Table 5.32) show that participants who either agreed or strongly agreed that outdated models cause NPLs accounted for 78 percent of the sample and only a minority of five percent did not concur. An outdated model would be one without critical variables that detect credit risk, resulting in borrowers being accepted with no capacity to service their debts. This happens when banks take too long to review a loan model in a dynamic environment, both locally and globally. Essentially, the results imply that the state of the model should be reviewed to determine effectiveness.

There are, however, other scholars such as Beck, Jakubic and PiloIU (2013), who posit that GDP is also a factor that fuels NPLs in Europe. Another factor was observed by Islamonglu (2015), who states that adjusting interest rates upwards and public debt stock impact loan performance and not loan model. Therefore, NPLs cannot be wholly attributed to the loan model.

Table 5.33: Internally modified models result in quality loans

		Frequency	Valid Percent
Valid	Strongly agree	69	17
	Agree	185	46
	Neutral	120	30
	Disagree	23	6
	Strongly disagree	4	1
	Total	401	100
Missing	System	5	
Total		406	

The result (Table 5.33) shows that internally modified models found favour with many respondents (63 percent), whilst 37 percent were uncertain or disagreed. This is understandable, as internal models are designed by the bank, in line with: the bank's objectives; the credit policy objectives; the risk appetite of the bank; and international standards, as well as regulatory standards, and all other relevant factors.

Abdou and Pointon (2011) citing Ong, Huang and Tzeng (2005), reflect the same view that banks using their internal Credit Score model only select clients with good scores. Quercia and Ding (2009) put forth another reason for attaining high quality loans, asserting loan modification that includes capital reduction, impacts loan performance.

5.7 To enhance Loan Portfolio Management Models

The results pertaining to the fifth objective of this study are presented overleaf.

Table 5.34: The bank no longer uses model results

		Frequency	Valid Percent
Valid	Strongly agree	2	1
	Agree	54	14
	Neutral	98	24
	Disagree	205	51
	Strongly disagree	42	10
	Total	401	100
Missing	System	5	
Total		406	

The result (Table 5.34) indicates that the banks utilise loan model results as indicated by the majority of the participants, which accounted for 61 percent. Additionally, the results suggest the loan model outcome provides a baseline or starting point for lending decisions once loan evaluation has been undertaken. However, for a few participants who agreed with the notion, it means there are some banks that ignore model results, because they also consider other complementary factors, such as their long-term relationship or security availed by the borrower. Banks will enhance the loan model performance, should it produce results that do not protect the banks from NPLs.

The findings echo results from Bartolozzi *et al.* (2008), who established banks use model results, applying a methodical approach when assessing clients for loan decisions. Furthermore, Samreen *et al.* (2013) confirmed banks use model results to distinguish between bankable and non-bankable clients.

Table 5.35: The current model is affecting the credit culture

		Frequency	Valid Percent
Valid	Strongly agree	22	6
	Agree	164	41
	Neutral	190	48
	Disagree	22	5
	Strongly disagree	0	0
	Total	399	100
Missing	System	7	
Total		406	

The results (Table 5.35) reveal that 53 percent of respondents disagreed with the statement that the current model affects credit culture. This implies the current model does not impact credit culture. There were, however, 47 percent of the participants who felt the culture was impacted by the loan model. Credit culture is a system that ensures all money granted as loans is collected by the bank.

Rajput, Gupta and Chauhan (2012) and Yakubu and Affoi (2014) noted a positive relationship between model performance and credit culture. Therefore, guidance from the model should be accurate.

Table 5.36: There are too many Type i and Type ii errors from the current model

		Frequency	Valid Percent
Valid	Strongly agree	11	3
	Agree	82	21
	Neutral	266	66
	Disagree	36	9
	Strongly disagree	3	1
	Total	398	100
Missing	System	8	
Total		406	

The results (Table 5.36) show 76 percent of respondents disagreed these errors occurred (Type i and Type ii), whilst 24 percent felt there were some errors at loan evaluation stage. Type i errors are those that make a bad applicant look good and Type ii errors refer to those that make a good client look bad. Furthermore, the results suggest the lending personnel responsible for the modelling are competent and information fed into the system is accurate, thereby mitigating errors. In the event of errors, the bank will enhance the model to improve effectiveness.

Samreen and Zaidi (2012) and Samreen *et al.* (2013) obtained similar findings by recording no errors in their Credit Score models and having achieved 100 percent prediction accuracy. The model review on errors should, therefore, be ongoing, so banks do not misclassify clients.

Table 5.37: The internal or local model needs to be aligned to internationally developed models

		Frequency	Valid Percent
Valid	Strongly agree	83	21
	Agree	258	64
	Neutral	47	12
	Disagree	9	2
	Strongly disagree	3	1
	Total	400	100
Missing	System	6	
Total		406	

The results (Table 5.37) show a high number of the respondents (89 percent) noted the importance of aligning models to international standards. This alignment will enhance the model because of globalisation, while local borrowers are also affected by international events.

Corroborating the outcome, Mačerinskienė and Ivaškevičiūtė (2008) and Abdou and Pointon (2011) emphasised the need to meet international standards through use of unlimited variables when developing a model. Moreover, fundamentals applied internationally will augment and or leverage the local factors, making the model robust.

Table 5.38: The bank has identified a need to have more variables on the model

		Frequency	Valid Percent
Valid	Strongly agree	31	8
	Agree	224	55
	Neutral	131	33
	Disagree	14	4
	Strongly disagree	1	0
	Total	401	100
Missing	System	5	
Total		406	

The results (Table 5.38) reveal 63 percent of respondents agreed with the notion; thus, a positive response to the need for more variables in the model. Whilst 33

percent were unsure, only four percent disagreed with this notion. This outcome confirms there is no need to limit variables that influence model effectiveness. The world is evolving, with economies unstable; technological changes; climate change; and political challenges; as well as legal and societal issues that need a re-think in all aspects of our lives. Therefore, there is always a need to revisit the variables used in a model.

These results are in line with observations made by Abdou and Pointon (2011) and Samreen and Zaidi (2012) that there is no limit on variables to be incorporated in a model such as the Credit Score model. The authors emphasised the need to contextualise the environment and incorporate variables that impact loan model prediction capacity.

Table 5.39: The bank’s model does not fully accommodate all qualitative details.

		Frequency	Valid Percent
Valid	Strongly agree	14	4
	Agree	110	28
	Neutral	211	52
	Disagree	63	16
	Strongly disagree	2	0
	Total	400	100
Missing	System	6	
Total		406	

The result (Table 5.39) reflects as much as 68 percent of the participants are satisfied with their loan model capacity in accommodating qualitative data. This makes it imperative to ensure a model has capacity to accommodate all information that will make it effective and guide the bank in making informed decisions. Samreen and Zaidi (2012) citing Chijoriga (2011), stated the model can accommodate qualitative information that will then be reduced into Scores following its weighing.

Table 5.40: The bank's model is not cost effective

		Frequency	Valid Percent
Valid	Strongly agree	18	5
	Agree	153	38
	Neutral	194	48
	Disagree	34	9
	Strongly disagree	1	0
	Total	401	100
Missing	System	5	
Total		406	

The result (Table 5.40) indicates that the majority of respondents (57 percent) was not quite convinced their model was cost effective as they remained neutral or did not agree with the notion. However, 43 percent of participants feel their model is cost effective. The results are similar to Chandler and Coffman (1979 as cited in Al Amari 2002), and Chatterjeey *et al.* (2016), who confirmed that efficient processing time and subsequent minimisation of credit process costs impact and facilitate determination of a loan contract. Additionally, good scores influence the lender to grant lower interest rates, whilst high scores ignite higher interest rates to borrowers. This suggests the banks' loan model impacts cost to both lender and borrower.

5.8 Testing for reliability

For a study to be considered reliable, Jaggia and Kelly (2013) argue it is imperative to test construct reliability. To determine reliability, Wywial (2015) recommended the use of Cronbach's alpha. To this effect, this analysis was performed, using the standard acceptable alpha threshold at 0.70 (Wywial 2015). Furthermore, the corrected item-total correlation coefficient was calculated to determine the acceptable items for every construct. As stated by Field (2016), the study used the minimum allowed threshold of 0.30.

Correlation coefficients are pointers to the relationship strength between two dissimilar variables (Field 2016). The different levels of strengths (Table 5.41) are shown below:

Table 5.41: Coefficients Strength

Coefficient Interval	Correlation
0.00-0.199	Very Weak
0.20-0.399	Weak
0.40-0.599	Medium
0.60-0.799	Strong
0.80-1000	Very Strong

Source: Field (2016)

A positive relationship between two variables is indicated, by a correlation coefficient greater than zero, whilst a negative relationship is illustrated by a value less than zero, with a zero-value indicating there is no relationship between the two compared variables. It is important to calculate correlation coefficients to enable the measurement or establish the level or soundness of the relationship between two variables. This comparison can be used to determine how loans behave in relation to another loan class. The reliability test was performed for all eight research constructs, with a summary of results provided (Table 5.42) below, which shows all the constructs' alpha statistics are higher than the stipulated minimum of 0.70, indicating all eight study constructs were shown to be reliable.

Table 5.42: Reliability Test

Construct	ABBR.	N of Items	Cronbach's Alpha
Model Parameter Attributes Factor A	MAA	4	.864
Model Parameter Attributes Factor B	MAB	3	.821
Model Formula	MF	2	.793
Model Type	MT	2	.837
Efficiency Measures	EM	4	.780
Models Effectiveness Factor 1	MUA	5	.765
Models Effectiveness Factor 2	MUB	2	.818
Loan performance	LP	4	.794

5.9 Testing for Validity

Following the reliability test, a test for validity was done. The validation of constructs was achieved using CFA, proposed by Kline (2016). This was done using both

convergent and discriminant validity. While convergent validity tested how well each item converged to a construct, discriminant validity tested how divergent the constructs were from each other. The acronyms used in the Convergent validity Schedule are presented (Table 5.43) below.

Table 5.43: Acronyms used

MAA	Model Parameter Attributes Factor A
MAB	Model Parameter Attributes Factor B
MF	Model Formula
MT	Model Type
EM	Efficiency Measures
MJA	Model Effectiveness Factor 1
MJB	Model Effectiveness Factor 2
LP	Loan Performance

5.9.1 Convergent Validity

Convergent validity refers to the degree of relatedness of two measures of constructs that should be related, theoretically, which is the case (Sarstedt and Mooi 2014; Roy *et al.* 2016). Convergent validity was used because it establishes the convergence of a given set of items to the same construct or lack thereof. In this regard, a minimum of 0.50 should be adhered to for unstandardized path coefficients, while 0.40 should be the minimum standardised coefficient.

The guidelines provided by Chinomona *et al.* (2013) and Kline (2016) stipulate that to generate an accurate CFA, items that should be removed first are those that report loadings below the minimum acceptable threshold of 0.500, before CFA is run. This work undertook an initial run and results (Table 5.44) show convergent validity in the first run was violated.

Table 5.44: Convergent Validity

			Estimate	Standardised	S.E.	C.R.	P
MAA1	<---	MAA	1.000	.575			
MAA2	<---	MAA	.890	.696	.091	9.800	***
MAA3	<---	MAA	.516	.325	.094	5.508	***
MAA4	<---	MAA	.423	.421	.061	6.878	***
MAA5	<---	MAA	.586	.422	.085	6.892	***
MAB1	<---	MAB	1.000	.430			
MAB2	<---	MAB	1.212	.555	.246	4.936	***
MAB3	<---	MAB	.943	.487	.195	4.829	***
MF1	<---	MF	1.000	.590			
MF2	<---	MF	1.325	.692	.131	10.085	***
MF3	<---	MF	-.390	-.293	.077	-5.087	***
MT1	<---	MT	1.000	.586			
MT2	<---	MT	.184	.139	.067	2.730	.006
MT3	<---	MT	-.249	-.174	.073	-3.401	***
MT4	<---	MT	.934	.493	.106	8.833	***
EM1	<---	EM	1.000	.330			
EM2	<---	EM	2.174	.645	.387	5.610	***
EM3	<---	EM	.193	.066	.167	1.158	.247
EM4	<---	EM	1.330	.423	.271	4.899	***
EM5	<---	EM	1.728	.487	.334	5.179	***
MUA1	<---	MUA	1.000	.663			
MUA2	<---	MUA	.762	.575	.077	9.881	***
MUA3	<---	MUA	1.103	.681	.097	11.376	***
MUA4	<---	MUA	.648	.510	.073	8.890	***
MUA5	<---	MUA	.803	.535	.087	9.281	***
MUB1	<---	MUB	1.000	.738			
MUB2	<---	MUB	1.044	.776	.096	10.826	***
LP1	<---	LP	1.000	.542			
LP2	<---	LP	.788	.500	.118	6.669	***
LP3	<---	LP	.805	.511	.119	6.752	***
LP4	<---	LP	.931	.506	.139	6.715	***
LP5	<---	LP	.302	.144	.128	2.350	.019

With respect to the items for the one factor of Model Attributes Factor 1, MAA, two of the items were below the prescribed minimum of 0.5, namely MAA3 ($B = 0.516$) and MAA4 (0.423). However, for Factor 2, none were below 0.50. For the second construct, MF, the only problem item was MF3 ($B = -0.390$), while for the construct, MT, there were two problem items, that is, MT2 ($B = 0.184$) and MT3 ($B = -0.249$). For the construct, EM, the item EM3 ($B = 0.193$) presented the only problem. There were no problems for MUA and MUB, but for Loan performance (LP), the problem

item was LP5 ($B = 0.302$). All the problem items with poor path coefficients were ultimately excluded from the model and the CFA yielded revised results (Table 5.45). Average scores or the cut-off point used was 0.60.

Table 5.45: Revised Convergent Validity

		Estimate	Standardised	S.E.	C.R.	P
MAA1	<--- MAA	1.000	.539			
MAA2	<--- MAA	.963	.706	.104	9.292	***
MAA3	<--- MAA	.518	.406	.101	5.128	***
MAA5	<--- MAA	.644	.436	.094	6.848	***
MAB1	<--- MAB	1.000	.404			
MAB2	<--- MAB	1.227	.527	.259	4.737	***
MAB3	<--- MAB	1.068	.517	.226	4.723	***
MF1	<--- MF	1.000	.595			
MF2	<--- MF	1.345	.709	.133	10.128	***
MT1	<--- MT	1.000	.532			
MT4	<--- MT	.971	.466	.112	8.696	***
EM1	<--- EM	1.000	.431			
EM2	<--- EM	2.176	.646	.384	5.673	***
EM4	<--- EM	1.328	.422	.269	4.943	***
EM5	<--- EM	1.699	.480	.327	5.199	***
MUA1	<--- MUA	1.000	.664			
MUA2	<--- MUA	.757	.572	.077	9.845	***
MUA3	<--- MUA	1.100	.680	.097	11.363	***
MUA4	<--- MUA	.651	.513	.073	8.936	***
MUA5	<--- MUA	.806	.538	.086	9.319	***
MUB1	<--- MUB	1.000	.728			
MUB2	<--- MUB	1.072	.786	.104	10.336	***
LP1	<--- LP	1.000	.536			
LP2	<--- LP	.838	.526	.124	6.753	***
LP3	<--- LP	.840	.527	.124	6.759	***
LP4	<--- LP	.924	.497	.141	6.538	***

The above results (Table 5.45) show that one of the items had a path coefficient below the minimum threshold of 0.50, with the minimum observed being MAA3 ($b = 0.518$). For MAB, the minimum observed was for MAB1 ($B = 1.00$), while for MF, the minimum was for MF1 ($B = 1.00$). The same coefficient was observed for EM, where ME1 was also 1.00. As for MUA, the minimum coefficient was MUA4 ($B = 0.651$). With respect to the construct MUB, the minimum coefficient was for MUB1 ($B = 1.00$) and last, for LP, the minimum was observed for LP2 ($B = 0.838$).

From the foregoing findings, no path coefficients were less than 0.50 and the study, in this respect, confirms no violation of convergent validity. As a result, no further item was removed. The resultant CFA model is presented (Figure 5.5) below.

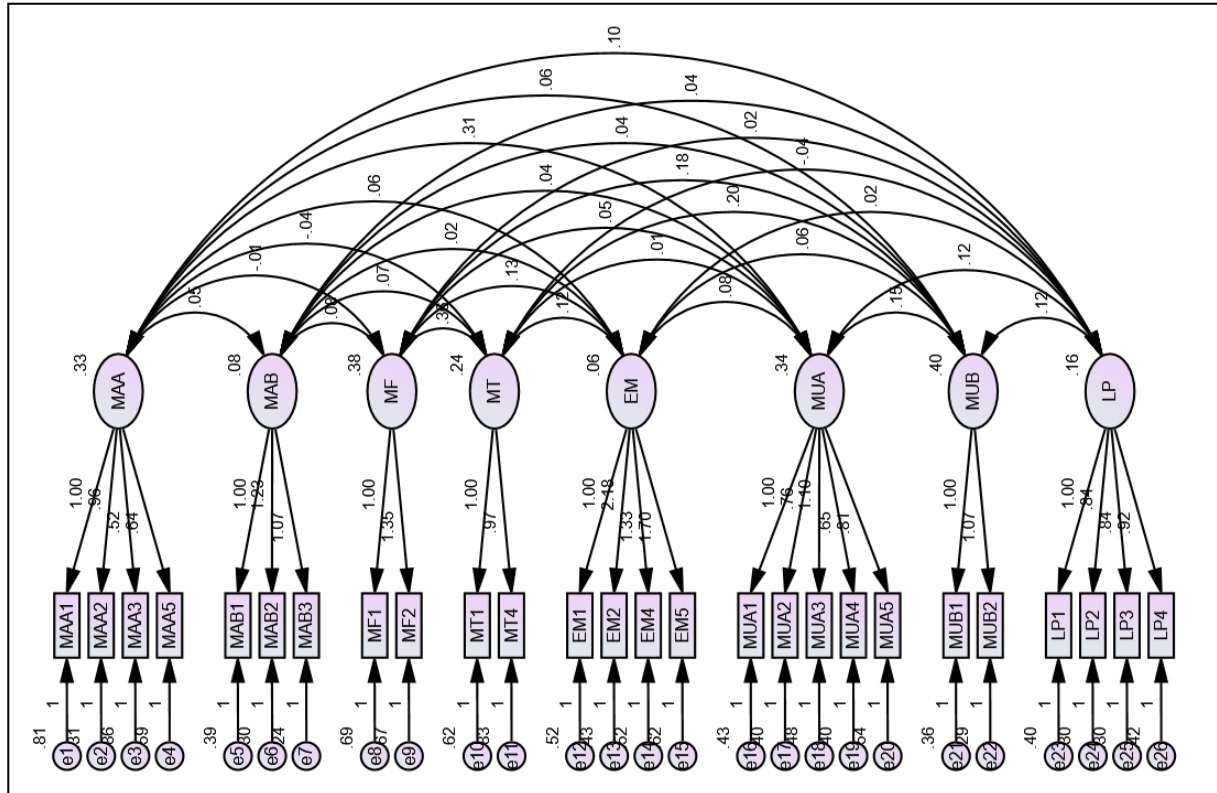


Figure 5.5: Confirmatory Factor Analysis Measurement Model

The bidirectional arrows between the oval latent variables represent the covariates for convergent validity, while the unidirectional arrows between the oval latent variables and rectangle items represent the path coefficients for convergent validity (Figure 5.5). It is evident from the outcome, with respect to convergent validity, the least path coefficient (from the oval latent variables to the rectangle items) was 0.651, for MUA4, followed by 0.757 for MUA2, thus evidencing validity.

5.9.2 Discriminant Validity

Discriminant validity tests constructs that should have no relationship do, in fact, not have any relationship (Farrell 2010). The discriminant validity test was used because it establishes whether the model constructs are highly correlated. Furthermore, this type of validity further ascertains whether there is a distinction between any two given

constructs, as should be the case (Kline 2016). The co-variances are set out (Table 5.46) below.

Table 5.46: Discriminant Validity

			Estimate	S.E.	C.R.	P
MAA	<-->	MAB	.051	.017	3.030	.002
MAA	<-->	MF	-.013	.028	-.475	.635
MAA	<-->	MT	-.038	.028	-1.337	.181
MAA	<-->	EM	.059	.016	3.669	***
MAA	<-->	MUA	.314	.042	7.558	***
MAA	<-->	MUB	.060	.027	2.183	.029
MAA	<-->	LP	.104	.023	4.535	***
MAB	<-->	MF	.078	.020	3.831	***
MAB	<-->	MT	.069	.019	3.603	***
MAB	<-->	EM	.024	.008	2.845	.004
MAB	<-->	MUA	.042	.015	2.803	.005
MAB	<-->	MUB	.037	.016	2.342	.019
MAB	<-->	LP	.035	.012	2.920	.004
MF	<-->	MT	.356	.045	7.872	***
MF	<-->	EM	.131	.026	4.974	***
MF	<-->	MUA	.045	.027	1.691	.091
MF	<-->	MUB	.184	.034	5.380	***
MF	<-->	LP	.016	.020	.796	.426
MT	<-->	EM	.119	.024	4.974	***
MT	<-->	MUA	.006	.026	.233	.816
MT	<-->	MUB	.195	.034	5.812	***
MT	<-->	LP	-.043	.021	-2.088	.037
EM	<-->	MUA	.079	.018	4.488	***
EM	<-->	MUB	.062	.016	3.804	***
EM	<-->	LP	.022	.010	2.327	.020
MUA	<-->	MUB	.155	.029	5.377	***
MUA	<-->	LP	.122	.022	5.452	***
MUB	<-->	LP	.117	.023	4.983	***

In order to meet the discriminant validity assumption, the covariances or heterotrait-monotrait (HTMT) ratio of correlations must be lower than 0.85, according to Gana and Broc (2019). The above test results (Table 5.46) indicate the highest covariance at 0.363, between the constructs MF and MT, while the second highest 0.318 was

between the constructs MAA and MUA. With none of these covariances greater than the maximum prescribed 0.85, thus not violating the discriminant validity assumption. Therefore, in confirming both convergent and discriminant validity, the construct validity was also confirmed.

The process followed was to test the objectives of the study, which started from section B of the questionnaire, with all responses rated in a 5-point Likert Scale.

5.10 Testing for Objective 1

The first research objective sought to establish whether LPMMs do exist and are applied in the Commercial Banks in Zimbabwe. To achieve this, three aspects were considered and these were the type of formula, the type of model, as well as the measures of model efficiency used.

i. Type of Formula

The first aspect of the first objective was to determine the type of formulae used for loan performance determination. Three types of formulae were investigated, the Score sheet-based formula, the ratio-based formula as well as the multivariate-based formula. The results are presented (Table 5.47) below.

Table 5.47: Type of Loan Portfolio Model Formula

	N	Mean	SD	Skewness	Kurtosis
Score sheet	406	3.44	1.033	-.361	-1.141
Ratio	406	2.91	1.166	.249	-1.171
Multivariate formula	406	4.15	.811	-1.067	1.530

The above results (Table 5.47) show the predominant loan model formulae used were based mainly on the multivariate formula ($M = 4.15$; $SD = 0.811$), while the second dominant were those based on the Score sheet ($M = 3.44$; $SD = 1.033$). The least dominant was based on the ratio formula, with a mean rating less than the midpoint 3.0 ($M = 2.91$; $SD = 1.166$). The fact that the multivariate formula had a positive kurtosis ($K = 1.530$) meant the distribution was leptokurtic and there was consensus among the respondents, as evidenced by the minimum standard deviation. There was, however, a huge discrepancy for the Score sheet and ratio

formula, both of which had negative kurtosis, thus, a platykurtic distribution, which meant the responses were not coherent (Houser 2016).

ii. Type of Model

The second aspect of the first objective sought to establish the type of model. Four main types of models were considered based on the literature review namely; the Credit Score model (internal), Z-score model, the Asset-Based model, as well as the use of various models on different loan products. The summary statistics are presented (Table 5.48) below.

Table 5.48: Type of Loan Portfolio Model

	N	Mean	SD	Skewness	Kurtosis
Z-Score Model	406	2.63	.930	.718	-.128
Asset-Based Model	406	3.65	.721	-.706	.940
Internal Credit Score Model	406	4.22	.780	-1.104	1.501
Various models on different loan products	406	3.31	1.031	-.256	-.663

The results (Table 5.48) show, of the four types of LPMs, 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 = 3.32; 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 to using this model, indicating very limited use in the Commercial Banks. It can, therefore, be argued more than one model is currently being used by Zimbabwe commercial banks. This puts to bed some assumption that the NPLs were caused by lack of lending tools used by the banks.

iii. Measures of Accuracy

The third aspect referred to the measures of accuracy and the results are presented (Table 5.49) below. From the outcome, the rating of all items was higher than the midpoint, with the rated measure of loan model accuracy that was the highest being the NPL ratio (M = 4.19; SD = 0.737), while the second highest was the defaults to performing assets ratio (M = 4.02; SD = 0.768). All had the least standard deviation and a very high kurtosis of 1.060 and 2.079 respectively. This shows very high coherence among the respondents. The third rated measures of accuracy were the Type i or Type ii errors (M = 3.31; SD = 0.856). The second least rated was the turnaround time of a bank (M = 3.21; SD = 0.900) and the least rated was low facility management costs (M = 3.12; SD = 0.799).

Table 5.49: Measures of Accuracy

	N	Mean	SD	Skewness	Kurtosis
Defaults to performing assets ratio	406	4.02	.768	-1.081	2.079
Type i/Type ii errors	406	3.31	.856	.195	-.133
Non-performing loan ratio	406	4.19	.737	-.832	1.060
Low facility management costs	406	3.12	.799	.047	.142
Turnaround time of a bank	406	3.21	.900	-.089	-.727

To establish the key factors that characterised these measures of accuracy, Exploratory Factor Analysis (EFA) was carried out using Principal component analysis (PCA). To validate the use of EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were performed. PCA is used to evaluate the underlying structure of three or more items and reduce the number of variables by systematically grouping the items depending with the magnitude of cohesion between them. This selection was largely as a result of the fact that the focus was on the identification of factors through dimension reduction, since this technique assumed that the items are statistically dependent of each other, unlike other techniques which assume the items are statistically independent of each other (Coolican 2014; Grolemond & Wickham 2017). The results are presented (Table 5.50) below.

Table 5.50: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.563
Bartlett's Test of Sphericity	Approx. Chi-Square	220.011
	Df	10
	Sig.	.000

The results (Table 5.50) show that KMO = 0.563 and since this was greater than 0.50, as advised by Keeves and Agresti (2018), this meant the data used had an adequate sample to conduct EFA. The KMO score measures whether the sample size being used for factor analysis is adequate or not. The minimum benchmark is 0.50 if the sample is good, but if the score is less than 0.5, this means that the sample is poor. Bartlett's test of sphericity was then computed using EFA, with a result of, $\chi^2(10) = 220.011$; $p = 0.000 < 0.05$, which was statistically significant, and this again meant the assumption was not violated. Communalities are presented (Table 5.51) below. None of the communalities were less than the expected minimum threshold of 0.40, proposed by Brown (2015). The items were, therefore, deemed to be significant and none of the items were dropped.

Table 5.51: Communalities - Measures of Accuracy

	Initial	Extraction
Defaults to performing assets ratio	1.000	.744
Type i/Type ii errors	1.000	.536
Non-performing loan ratio	1.000	.748
Low facility management costs	1.000	.516
Turnaround time of a bank	1.000	.566

Extraction Method: Principal Component Analysis

The corresponding scree plot is illustrated (Figure 5.6) below.

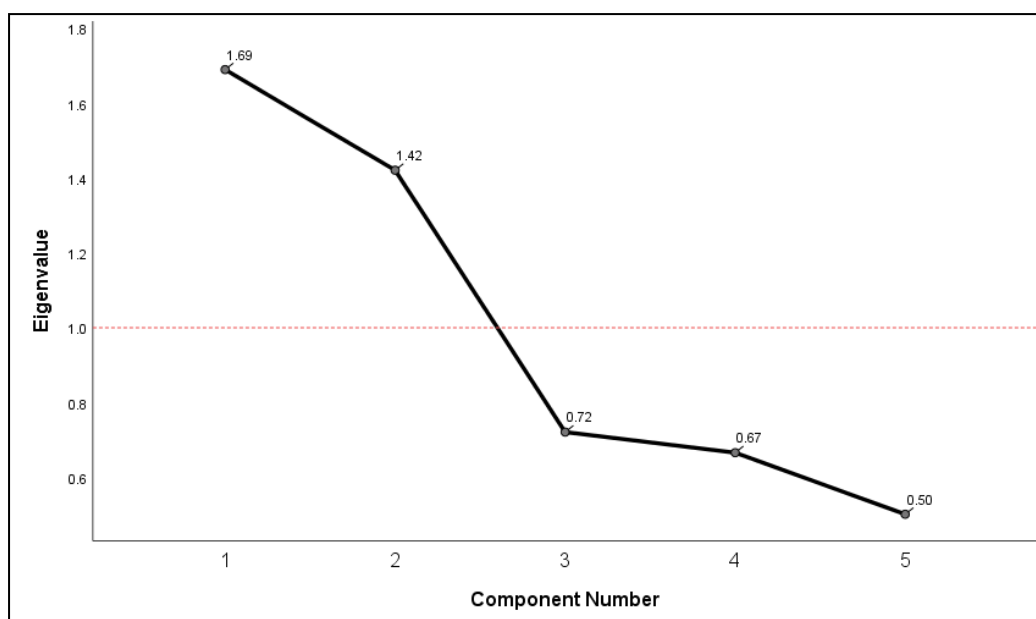


Figure 5.6: Scree Plot

The results (Figure 5.6) show only two components whose eigenvalues were greater than 1.0. The eigenvalue for component 1 was 1.690, while the eigenvalue for component 2 was 1.421. The total variance explained is set out (Table 5.52) below.

Table 5.52: 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	1.690	33.796	33.796	1.690	33.796	33.796	1.641	32.811	32.811
2	1.421	28.418	62.214	1.421	28.418	62.214	1.470	29.403	62.214
3	.721	14.427	76.641						
4	.666	13.326	89.967						
5	.502	10.033	100.000						

Extraction Method: Principal Component Analysis

The results show that component 1 explained 32.811 percent of the variance, while component 2 explained 29.403 percent. The cumulative variance explained was 62.214 percent and being greater than the minimum expected 40 percent, indicates the validity of extracted factors. The rotated component matrix is presented (Table 5.53) below.

Table 5.53: Rotated Component Matrix

	Component	
	1	2
Turnaround time of a bank	.750	.058
Type i/Type ii errors	.729	.066
Low facility management costs	.717	-.052
Non-performing loan ratio	-.094	.860
Defaults to performing loans ratio	.154	.849

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 3 iterations

The 0.50 minimum threshold was considered and using this benchmark, the first component comprised three items namely; turnaround time of a bank, Type i or Type ii errors and low facility management costs (Lyyra, Leskinen & Heikinaro-Johansson 2015; Kilic 2018; Shi, Maydeu-Olivares & DiStefano 2018). These measures related to the non-ratio-based measures of efficiency. With respect to the second component, the items with factor loadings greater than 0.50 were the NPL ratio, as well as defaults to performing loans ratio. Both items were ratio-based measures of accuracy.

Therefore, in line with both the main research question and sub research question 1 the study argued that loan models such as Internal credit score, asset based, z score are used in Zimbabwe Commercial banks. Furthermore, as exhibited by accuracy measures, there is a positive correlation relationship between loan model accuracy and loan performance in Zimbabwe Commercial banks. The study also revealed that internal credit score for corporates is the model of choice by most Commercial banks, henceforth, closing a gap on the most suitable loan model to be used by a commercial bank in Zimbabwe.

5.11 Testing for Objective 2

The second research objective sought to examine the LPMM parameter attributes currently used by Commercial Banks in Zimbabwe. Additionally, the results answered the study main research question and sub research question; “Which parameter

attributes do the commercial banks in Zimbabwe consider in LPM model 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, with a view to establishing the principal factors that emerged from the model parameters.

5.11.1 Descriptive Statistics

The summary statistics (Table 5.54) used for the model parameter rating are presented below.

Table 5.54: Summary Statistics

	N	Mean	SD	Skew	Kurt
The bank uses Industry based parameters	406	3.89	.686	-1.094	3.309
Past loan performance experienced is considered in setting parameters	406	3.96	.645	-1.131	3.490
Parameters are author based initiated by bank or consultant	406	3.49	.851	-.203	-.623
The model can incorporate sizeable factors such as financial/behavioural	406	3.85	.572	-.634	1.986
Outcome probabilities of the model are pre-defined	406	3.71	.786	-.781	.433
A model's output can be ranked	406	4.03	.616	-.722	2.110
The model's benchmark is well-defined	406	3.32	1.068	-.129	-1.114
The model is robust and is not reviewed or replaced	406	3.50	.976	-.458	-.728

The ratings were based on a 5-point Likert scale and the findings show all ratings 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 past 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 (Field 2016). The second least-rated item related to model parameters initiated by 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.

5.11.2 Factor Analysis

Factor analysis is a collection of methods used to examine how underlying constructs influence the responses on several measured variables (Hinton, Brownlow & McMurray 2004; Howitt & Cramer 2020). The foregoing list indicates respondents used these attributes at varying levels. In grouping or classifying similar model parameter attributes together into dimensions, it was imperative to use dimension reduction techniques as advised by Brown (2015). In this regard, EFA was used. To validate the use of factor analysis, the KMO test for adequacy of the sample and Bartlett's test for sphericity were performed, with results shown (Table 5.55) below.

Table 5.55: KMO Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.657
Bartlett's Test of Sphericity	Approx. Chi-Square	379.009
	Df	28
	Sig.	.000

According to Garson (2012), the ideal KMO statistic should be greater than 0.50. In the results above the KMO was 0.657, while for Bartlett's test, $\chi^2 (28) = 379.009$; $p < 0.05$. This confirmed the data used for factor analysis met the sampling adequacy requirement. Grolemond and Wickham (2017) posited that to extract the factors, PCA must be used as extraction method. Taking the advice of Thompson (2018), the Varimax orthogonal rotation method was used instead of the oblique methods, since

the study did not assume the factors would be correlated. The resultant communalities are summarised (Table 5.56) below.

Table 5.56: Communalities

	Initial	Extraction
The bank uses Industry based parameters	1.000	.527
Past loan performance experienced is considered in setting parameters	1.000	.512
Parameters are author based initiated by bank or consultant	1.000	.485
The model can incorporate sizeable factors such as financial/behavioural	1.000	.526
Outcome probabilities of the model are pre-defined	1.000	.565
A model's output can be ranked	1.000	.628
The model's benchmark is well-defined	1.000	.631
The model is robust and is not reviewed/replaced	1.000	.473
Extraction Method: Principal Component Analysis		

According to Dugard, Todman and Staines (2010), communalities measure the underlying latent continua, that is, the amount of variance in each variable accounted for by the rest of the items (shared variance) and the minimum communality extraction should be 0.40. The extracted communalities (Table 5.56) were all above this threshold, with the minimum observed being 0.473. This shows all the attributes listed were important in factor determination. The corresponding scree plot is illustrated (Figure 5.7) below.

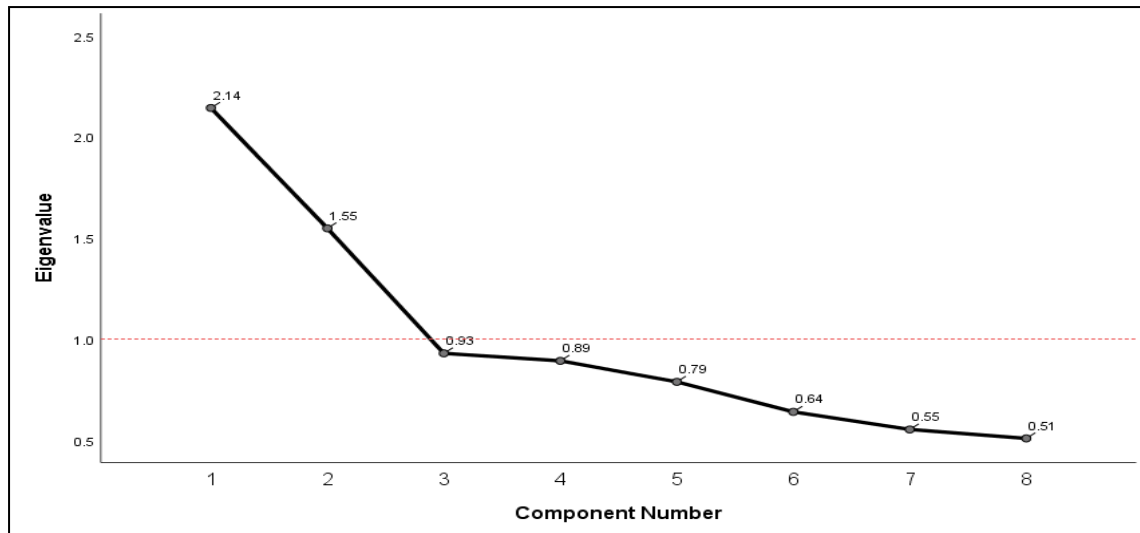


Figure 5.7: Scree Plot

Brown (2015, cited in Howitt, & Cramer 2020) states for a factor to be valid, it ought to have an eigenvalue greater than 1.0. From the scree plot (Figure 5.7) only two constructs (1.55 and 2.14) were extracted and the eigenvalue for both was above 1.0. The resultant total variance explained is presented (Table 5.57). Construct 1 had an eigenvalue of 2.143 and accounted for a variance of 24.384 percent, while Construct 2 had an eigenvalue of 1.548 and accounted of a variance of 21.746 percent (Figure 5.7). The cumulative variance explained by these two factors was 46.130 percent and, being greater than 40 percent, it confirmed these were valid factors. Kilic (2018) and Shi *et al.* (2018) concurred that 0.50 is considered the standard cut-off point for the extracted components' inclusion criteria.

Table 5.57: Total Variance Explained

#	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	2.143	26.786	26.786	2.143	26.786	26.786	1.951	24.384	24.384
2	1.548	19.344	46.130	1.548	19.344	46.130	1.740	21.746	46.130
3	.929	11.613	57.743						
4	.892	11.149	68.893						
5	.788	9.852	78.744						
6	.640	7.994	86.738						
7	.553	6.908	93.646						
8	.508	6.354	100.000						

Extraction Method: Principal Component Analysis

Upon rotation of these factors, the items with factor loadings that met these criteria are presented (Table 5.58) below.

Table 5.58: Rotated Component Matrix

	Component	
	EBA	EBA
The model's benchmark is well-defined	.775	-.176
Outcome probabilities of the model are pre-defined	.697	.281
The model is robust and is not reviewed/replaced	.571	-.272
A model's output can be ranked	.541	.318
Parameters are author based initiated by bank or consultant	.463	.365
The bank uses Industry based parameters	-.119	.716
Past loan performance experienced by bank is considered in setting parameters	.099	.709
The model can incorporate sizeable factors such as financial/behavioural	.088	.554

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 3 iterations

Factor 1, whose rotated sums of squared loadings was high (24.384 percent), is shown by the results to comprise these items: the model's benchmark is being well-defined; outcome probabilities of the model are pre-defined; the model is robust and

is not replaced; and the model's output is ranked; as well as the parameters are author-based, initiated by bank or consultant. Four of the items are related to benchmarking attributes, as they invariably mentioned outcome probabilities, robustness and model outputs. However, Factor 2, whose rotated sums of squared loadings was barely 21.746 percent, comprised only three items and these were: industry-based parameters being used, past loan performance experience considered when setting parameters, as well as the model being able to incorporate sizeable factors such as financial and behavioural characters. The second factor related to experience-based attributes, as the parameters extracted comprise attributes based on experience.

These results reflect that loan model parameter attributes impact loan performance. The study argued that as long as the parameter attribute remains relevant it will influence accurate prediction of loan performance. The outcome puts forward the following parameter attributes as outstanding; ability to rank the model outcome, consideration of past experience, use of industry-based parameters, as well as the ability of the model to incorporate sizeable factors. This settled the confusion about which attributes mostly influence loan model selection and satisfactorily address the sub-research question on parameter attributes, hence, closing the gap on what fundamentals the banks should consider as a priority when developing or enhancing a loan model.

5.12 Testing for Objective 3

The aim of the third research objective was 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 5.59).

Table 5.59: 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 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 assessment of 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 performing loan to the total loan book	406	4.13	.742	-1.313	3.610
To predict bankruptcy	406	3.63	.876	-.869	-.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 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 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 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 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.

5.12.1 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, as well as Bartlett's test for sphericity were performed and the outcome (Table 5.60) presented.

Table 5.60: 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 the Bartlett's test significance being less than the prescribed 0.05, the results confirmed the assumptions for the use of EFA were not violated. The PCA was used as extraction method and Varimax orthogonal rotation method was performed (Thompson 2018). Communalities are presented (Table 5.61) below.

Table 5.61: Communalities

	Initial	Extraction
To identify good clients	1.000	.518
To ensure security adequacy	1.000	.530
To determine 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 on assessment of sister companies of a borrowing corporate client	1.000	.090
To determine non-performing loan	1.000	.578
To compare 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 communality extraction less than the prescribed minimum of 0.40, the item “to guide on assessment of sister companies of a borrowing corporate client”, whose communality was 0.090 and flagged as a possible item for deletion. The extracted components are shown (Figure 5.8) below.

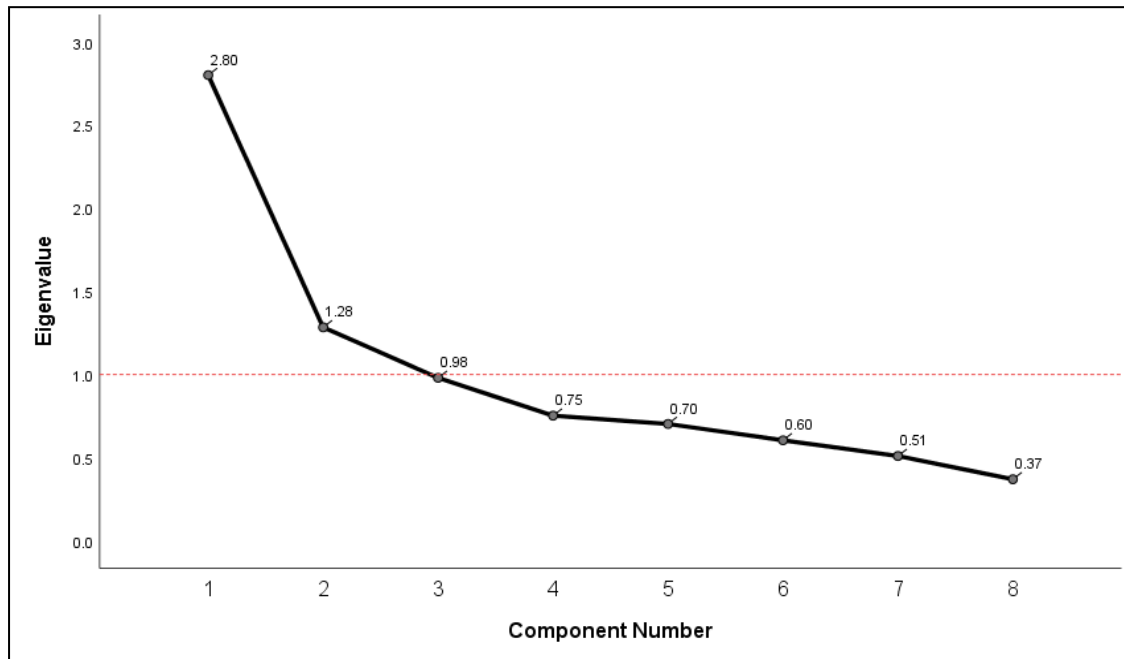


Figure 5.8: Scree Plot

There were only two components extracted with eigenvalues greater than the recommended value of 1.0 (Brown 2015; Keller 2021). The rotation sums of their squared loadings and total variance explained are presented (Table 5.62) below.

Table 5.62: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	% of Variance			% of Variance			% of Variance		
	Total	e	Cumulative %	Total	e	Cumulative %	Total	e	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 percent. For component 2 the eigenvalue was $\lambda = 1.284$ and the variance explained was 20.817 percent. Overall, the cumulative variance explained was 51.068 percent and, since this was greater than the minimum expected value of 40 percent, it meant the extracted components were valid. The rotated component matrix is presented (Table 5.63) below.

Table 5.63: Rotated Component Matrix

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

Rotation converged in 3 iterations

Kilic (2018) and Shi *et al.* (2018) recommend the factor loadings ought to 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 on assessment of sister companies of a borrowing corporate client”, which had earlier been flagged for having a poor communality. 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 factor one comprised proactive measures that impact loan model effectiveness. Likewise, identifying the common issues among the component 2 items shows that factor two comprised reactive measures.

5.12.2 Loan Performance

The last aspect of the third research objective was aimed at evaluating loan performance, which was measured on a 5-point variable response Likert scale with the statistics summary presented (Table 5.64) below.

Table 5.64: 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

The results (Table 5.64) 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 that "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 least 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 overwhelmingly 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 used by banks to determine effectiveness of loan models. The results address the research sub-question on methods used to measure effectiveness of loan models.

5.13 Testing for Objective 4

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. The basis of these factors was explained in the previous chapter.

While the variables could have been tested separately per the advice of Field (2016), the independent variables often have relationships among themselves and testing the relationships separately does not take cognisance of the influence of other variables that make separate tests flawed. In this regard, all the variables were tested holistically in 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, Wang and Wang (2019) further argued that tests done separately are not comparable, however, 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 single SEM.

According to Kline (2016, cited in Stephens 2020), it is imperative to first validate these constructs prior to 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 research constructs using CFA, the research hypotheses were then tested. Since the research comprised of latent variables that were measured, each research construct was tested for several items, use of SEM was considered as the most robust approach, in lieu of multiple linear regression techniques.

5.13.1 Structural Equation Modelling (SEM)

According to Hair *et al.* (2014) and Bartolucci, Bacci and Gnadi (2022), 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) 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 by means of 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 5.9) below.

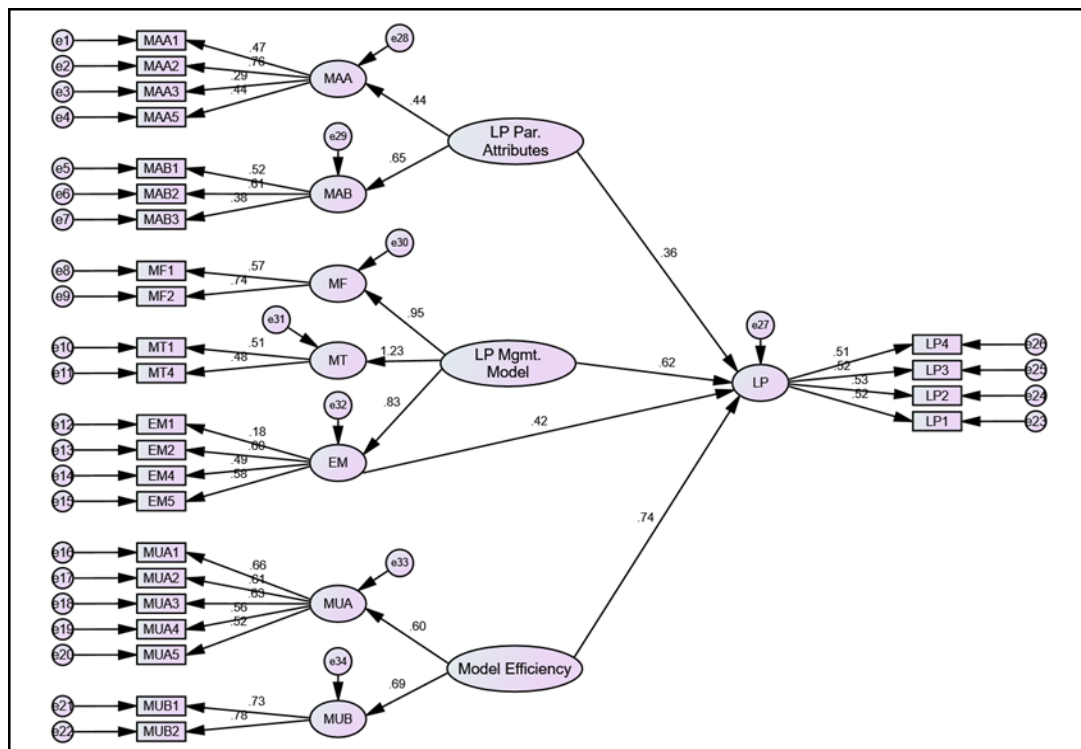


Figure 5.9: Structural Equation Model (SEM)

The latent independent variables are depicted in oval shape and the constituent items are represented by rectangles, while the error terms are represented by the circles (Figure 5.9) as advised by Hair *et al.* (2014) and Kline (2016). The corresponding coefficients from the latent variables pointing in the direction of LP, are presented (Table 5.65) below.

Table 5.65: Structural Equation Model – Coefficients

			Estimate	Standardised	S.E.	C.R.	P
EM	<---	LPMM	1.000	.830			
LP	<---	LPMA	.603	.357	.316	1.988	.046
LP	<---	LPMM	2.038	.616	.982	2.075	.038
LP	<---	LME	.654	.736	.146	4.479	***
MUB	<---	LME	1.000	.687			
MUA	<---	LME	.796	.601	.165	4.832	***
MT	<---	LPMM	4.992	1.231	1.652	3.022	.003
MF	<---	LPMM	4.754	.946	1.591	2.987	.003
MAB	<---	LPMA	1.000	.651			
MAA	<---	LPMA	.978	.444	.539	1.813	.070
LP	<---	EM	1.153	.420	.761	2.915	.003

R² = 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, $\beta = 0.420$ ($p = 0.003 < 0.05$). 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 Goodness of Fit test results are presented (Table 5.66).

Table 5.66: Model Fit Results

CMIN	NPAR	CMIN	DF	P	CMIN/DF
Default model	63	742.643	288	.000	2.679
Saturated model	351	.000	0		
Independence model	26	3050.400	325	.000	9.386
Baseline Comparisons	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.908	.844	.916	.917	.925
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000
RMSEA	RMSEA	LO 90	HI 90	PCLOSE	
Default model	.072	.067	.077	.000	
Independence model	.144	.139	.149	.000	
Parsimony Measures	PRATIO	PNFI	PCFI		
Default model	.886	.750	.792		
Saturated model	.000	.000	.000		
Independence model	1.000	.000	.000		

The above outcome shows the relative Chi-square was $CMIN/DF = 2.679$, which is below the maximum threshold of 3.0 (Thompson 2018). 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 (Hair *et al.* 2009; Kline 2016; Thompson 2018). With regard to 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 (Roy *et al.* 2016). Last, the Root Mean Square Error of Approximation was $RMSEA = 0.072$, thus, less than 0.08, which is the maximum prescribed (Hair *et al.* 2014; Kline 2016; Brase & Brase 2021). Therefore, as all the Goodness-of-Fit tests fall within the thresholds expected, the SEM would, therefore, have a very good fit. This means the model can be considered consistent with the empirical data. These good model fit indices demonstrate validity of the empirical model proposed in this study.

This study has thus shown that the independent variables influence loan models, hence, influencing 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 onset.

5.14 Testing for Objective 5

The fifth research objective sought to identify circumstances that motivate Commercial Banks to enhance their LPMMs, leading to the development of an own model and to confirm whether a 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 5.10) below.

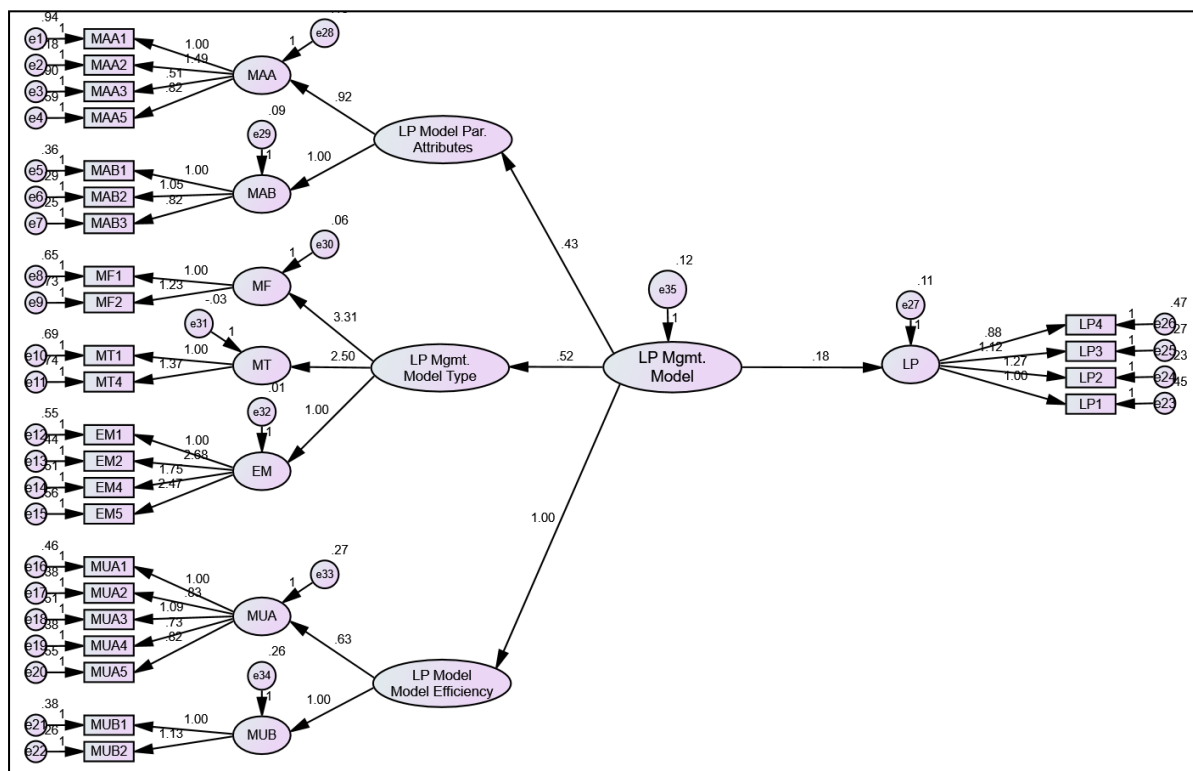


Figure 5.10: Structural Equation Model (Overall Dimensions)

The results (Table 5.67) 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.

Table 5.67: Structural Equation Model - Coefficients

	Estimate	Standardised	S.E.	C.R.	P
LPMU <--- LPMM	1.000	1.000			
LPMMT <--- LPMM	.521	1.000	.135	3.866	***
LPMA <--- LPMM	.429	1.000	.108	3.960	***
MUB <--- LPMU	1.000	.556			
MUA <--- LPMU	.632	.386	.139	4.539	***
EM <--- LPMMT	1.000	.893			
MT <--- LPMMT	2.496	1.073	.616	4.052	***
MF <--- LPMMT	3.315	.927	.790	4.198	***
MAB <--- LPMA	1.000	.446			
MAA <--- LPMA	.922	.306	.318	2.896	.004
LP <--- LPMM	.183	.187	.076	2.400	.016
MAA1 <--- MAA	1.000	.416			
MAA2 <--- MAA	1.494	.846	.299	4.996	***
MAA3 <--- MAA	.514	.234	.139	3.700	***
MAA5 <--- MAA	.821	.429	.145	5.653	***
MAB1 <--- MAB	1.000	.482			
MAB2 <--- MAB	1.049	.538	.221	4.745	***
MAB3 <--- MAB	.816	.472	.174	4.701	***
MF1 <--- MF	1.000	.621			
MF2 <--- MF	1.235	.679	.131	9.430	***
MT1 <--- MT	1.000	.449			
MT4 <--- MT	1.366	.552	.186	7.326	***
EM1 <--- EM	1.000	.262			
EM2 <--- EM	2.680	.629	.616	4.348	***
EM4 <--- EM	1.747	.439	.433	4.036	***
EM5 <--- EM	2.471	.551	.581	4.256	***
MUA1 <--- MUA	1.000	.641			
MUA2 <--- MUA	.833	.607	.093	8.999	***
MUA3 <--- MUA	1.089	.650	.116	9.363	***
MUA4 <--- MUA	.730	.555	.086	8.462	***
MUA5 <--- MUA	.819	.528	.101	8.145	***
MUB1 <--- MUB	1.000	.708			
MUB2 <--- MUB	1.133	.808	.144	7.892	***
LP1 <--- LP	1.000	.448			
LP2 <--- LP	1.275	.670	.216	5.901	***
LP3 <--- LP	1.119	.587	.188	5.954	***
LP4 <--- LP	.876	.394	.176	4.992	***

The Goodness-of-Fit test results are presented (Table 5.68) below. 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 *et al.* 2014; Kline 2016; Thompson 2018). 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 (Roy *et al.* 2016). Last, the Root Mean Square Error of Approximation was RMSEA = 0.052, which was less than the 0.08 maximum prescribed (Hair *et al.* 2014; Kline 2016; Brase & Brase 2021).

Table 5.68: Model Fit Results

CMIN	NPAR	CMIN	DF	P	CMIN/DF
Default model	60	727.280	291	.000	2.499
Saturated model	351	.000	0		
Independence model	26	3050.400	325	.000	9.386
Baseline Comparisons	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.907	.941	.952	.8493	.946
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000
RMSEA	RMSEA	LO 90	HI 90	PCLOSE	
Default model	.052	.047	.068	.000	
Independence model	.144	.139	.149	.000	
Parsimony Measures	PRATIO	PNFI	PCFI		
Default model	.895	.747	.789		
Saturated model	.000	.000	.000		
Independence model	.895	.747	.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.

The study also evaluated model areas of improvement, with respondents asked to rate the possible areas of improvement on a 5-Point variable response Likert scale and results summarised (Table 5.69) below.

Table 5.69: Model Areas of Improvement

	N	Mean	SD	Skew	Kurt
The bank no longer uses model results	406	2.46	.909	.598	-.063
The current model is affecting the credit culture	406	3.50	.709	.164	-.235
There are too many Type i and Type ii errors from the current model	406	3.19	.687	.468	1.261
The internal or local model needs to be aligned to internationally developed models	406	4.04	.700	-.962	2.625

The bank has identified a need to have more variables on the model	406	3.69	.690	-.319	.339
The bank's model does not fully accommodate all qualitative details	406	3.20	.776	.201	-.040
The bank's model is not cost effective	406	3.41	.737	.047	-.086

From the results it is shown the statement “the bank no longer uses the model results” had the least rating ($M = 2.46$; $SD = 0.909$). Furthermore, with the mean rating less than the midpoint of 3.0, this meant the banks were in fact using the LPMM results, even though not all did. The kurtosis was -0.063, which is close to 0.00, inferring the response distribution was mesokurtic, meaning a moderate degree of coherence. In other words, while some banks were using the model results, some did not, identifying the need for all the banks to use the results.

Respondents, however, did concur that internal or local models need to “be aligned with internationally developed models” ($M = 4.04$; $SD = 0.700$). This indicated a lack of international variables for LPMMs developed in Zimbabwe. A huge gap existed, with the second highest rating of $M = 3.69$ ($SD = 0.690$) the recommendation that “the bank has identified the need to have more variables” on the LPMM. The third highest area of improvement was that the “current model was affecting the credit culture” ($M = 3.50$; $SD = 0.709$), while the fourth highest was that the bank's LPM is “not cost effective” ($M = 3.41$; $SD = 0.737$). The bank's LPMM “does not fully accommodate all qualitative details” was ranked fifth ($M = 3.20$; $SD = 0.776$), while the sixth highest rating was “too many Type i and Type ii errors” from the current LPMM ($M = 3.19$; $SD = 0.687$).

5.14.1 Factor Analysis

Having reviewed the descriptive statistics relating to the model areas of improvement the study, furthermore, went on to establish any possible broad areas of improvement; to be achieved through dimension reduction, according to Field (2016) as well as Howitt and Cramer (2020). To validate the use of factor analysis, as was the case with the preceding factor analysis, the KMO measure of sampling adequacy and Bartlett's test of sphericity were carried out. The results for the two tests are presented (Table 5.70) below.

Table 5.70: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.634
Bartlett's Test of Sphericity	Approx. Chi-Square	406.856
	Df	21
	Sig.	.000

The findings reveal a KMO = 0.634, being greater than 0.50 this meant the sample used had an adequate sample for conducting EFA (Keeves & Agresti 2018). Bartlett's test of sphericity, χ^2 (21) = 406.856; and $p = 0.000 < 0.05$, thus, the assumption for sphericity was not violated. With both assumptions validated, the study proceeded with the EFA and resultant communalities presented (Table 5.71) below.

Table 5.71: Communalities

	Initial	Extraction
The bank no longer uses model results	1.000	.751
The current model is affecting the credit culture	1.000	.530
There are too many Type i and Type ii errors from the current model	1.000	.566
The internal or local developed models need to be aligned to internationally developed models	1.000	.556
The bank has identified need to have more variables on the model	1.000	.448
The bank's model does not fully accommodate all qualitative details	1.000	.476
The bank's model is not cost effective	1.000	.456

Extraction Method: Principal Component Analysis

The results show none of the communalities were less than the expected 0.40 minimum threshold (Brown 2015; Howitt & Cramer 2020). Therefore, none of the items were dropped. The scree plot shows the extracted factors (Figure 5.11).

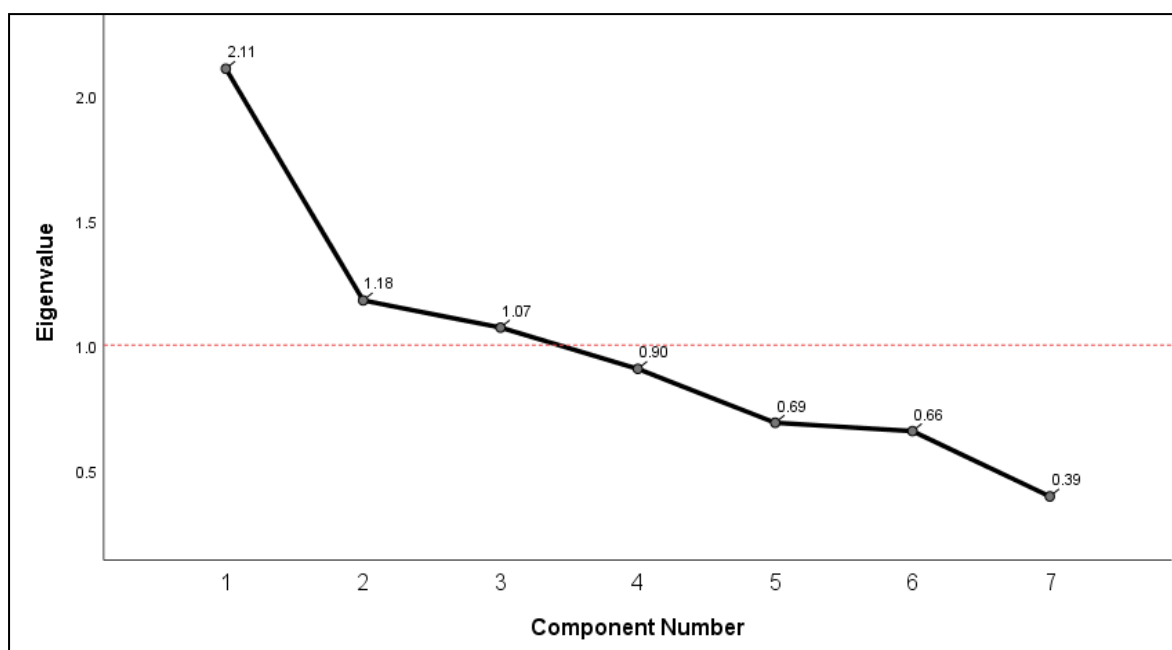


Figure 5.11: Scree Plot

There were three components with eigenvalues greater than 1.0 (Figure 5.11). The eigenvalue for component 1 was 2.11, while the eigenvalue for component 2 was 1.18 and for component 3, this was 1.07. The total variance explained is tabulated (Table 5.72).

Table 5.72: 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	2.107	30.104	30.104	2.107	30.104	30.104	1.660	23.707	23.707
2	1.179	16.846	46.950	1.179	16.846	46.950	1.586	22.658	46.365
3	1.070	15.291	62.241	1.070	15.291	62.241	1.111	15.875	62.241
4	.905	12.926	75.167						
5	.689	9.843	85.010						
6	.655	9.363	94.373						
7	.394	5.627	100.000						

Extraction Method: Principal Component Analysis

The variance explained for component 1 was 23.707 percent, while component 2 explained a variance of 22.658 percent and for component 3, the variance explained was 15.875 percent. Overall, the cumulative variance explained was 62.241 percent.

This was greater than the 40 percent minimum threshold and, in this regard, the study has confirmed the extracted factors as valid (Kilic 2018). The rotated component matrix is presented (Table 5.73) below.

Table 5.73: Rotated Component Matrix

	Component		
	1	2	3
The bank no longer uses model results	.861	.161	-.080
There are too many Type i and Type ii errors from the current model	.803	.103	.173
The current model is affecting the credit culture	.170	.717	.093
The bank's model is not cost effective	.195	.669	-.297
The internal or locally developed models needs to be aligned to internationally developed models	-.241	.615	.293
The bank's model does not fully accommodate all qualitative details	.365	.150	.821
The bank has identified need to have more variables on the model	.119	-.089	.728

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 12 iterations.

The minimum factor loadings threshold considered was 0.5 (Pearce 2013; Jaggia & Kelly 2013; Field 2016; Howitt & Cramer 2020). Using these criteria, two items were loaded under Factor 1 namely, “the bank no longer uses model results” and “there are too many Type i and Type ii errors from the current model”. These items related to model non-usage and model errors and in this regard, this factor was labelled **Model Accuracy**.

Three items were loaded under Factor 2 and these were; ‘the current model is affecting the credit culture’, ‘the bank’s model is not cost effective’ and ‘the internal or local models needs to be aligned to internationally developed models’. These three items related to the effect of the models on issues such as cost and credit culture and, in this respect, was labelled **Model Efficiency**. For the third component there were two items, that is, “the bank’s model does fully accommodate all qualitative details” and that “the bank needs to have more variables on the model”. These two items identified the deficiencies in the models being used and the study has to, in this regard, label these two as **Model Parameters**.

The study has argued that change of a loan model is largely influenced by model accuracy, efficiency and parameters under use. This also fully addressed the research question and sub-research question on influences of loan model replacement. The results will close the gap of speculation on why banks review and completely replace their loan models.

5.14.2 Empirical Results: Credit score model

To address the final aspect of the fifth research objective, which was to develop an Internal Credit Score model, the LR technique was used, by only retaining variables with the most significant influence in predicting default. The study placed reliance on system results.

5.14.3 Credit Score Model Diagnostic Tests

The LR model was estimated using the generalised linear models function in R (*glm*) and the summary of the results are shown (Figure 5.12) below:

```
all:
glm (formula = Default ~ ., family = "binomial", data = LRtrain)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3809036  0.2111166  0.3562901  0.5101748  3.0166470

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  4.55515195 12.49256402  0.36463 0.7153883
LoanAmt      -0.66933639  1.68895319 -0.39630 0.6918819
Monthly Revenue  2.79485887  9.61293700  0.29074 0.7712507
AmtOverdue    -0.08000233  0.02573696 -3.10846 0.0018806 **
Rating        0.96124630  1.19222637  0.80626 0.4200920
Tenure        -0.46540044  1.03643968 -0.44904 0.6534045
IntRate       6.71269087 13.66817793  0.49112 0.6233429
Age-Corporate -1.30304665  1.30646298 -0.99739 0.3185776

Security      -1.21524944  0.62584875 -1.94176 0.0521659 .
Economy       -0.29854135  0.94973386 -0.31434 0.7532612
Management    0.09426199  0.18804821  0.50127 0.6161846
Running Loans  0.46038863  0.72950099  0.63110 0.5279746
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 124.19993 on 122 degrees of freedom
```

```
Residual deviance: 78.59134 on 111 degrees of freedom  
AIC: 103.59134  
  
Number of Fisher Scoring iterations: 79
```

Figure 5.12: Logistic Regression Model Estimation

Source: R Script Output

The majority of the explanatory variables have statistically insignificant estimates as shown by the probability values. AmtOverdue is very significant, at one percent level, whilst Security is significant at 10 percent significance level. However, as in all other regression models, it is important a model be free from multicollinearity. Multicollinearity is a situation where two explanatory variables bring in same information into the model (Wooldridge 2013). The LR model should also be free from the effect of outliers in the data, hence, the model had to be tested for any correlations among regressors and extreme regressor values (outliers).

5.14.4 Testing for the existence of Outliers: The Dixon Test

A formal test for outliers was conducted using the XLStat package under the null hypothesis that the data has no extreme values and an alternative that there are outliers in the dataset. It is ideal all continuous variables be within acceptable range (that is, not too large). The summary below (Table 5.74) shows the formal tests for the existence of outliers.

Table 5.74: Dixon Test Result Statistics for LoanAmt

Dixon test for outliers / Two-tailed test (LoanAmt):	
R10 (Observed value)	0.171
R10 (Critical value)	0.192
p-value (Two-tailed)	0.085
Alpha	0.05

Source: R Script Output

From the above Table 5.74, a non-significant p-value (0.085) shows the extreme values in the LoanAmt series are non-significant, hence, we fail to reject the null hypothesis and conclude there are no outliers in the LoanAmt series.

Table 5.75: Dixon Test Summary Statistics – Monthly Revenue

Dixon test for outliers / Two-tailed test (Income):	
R10 (Observed value)	0.230
R10 (Critical value)	0.192
p-value (Two-tailed)	0.017

Source: R Script Output

The result (Table 5.75) reflects that the Monthly Revenue series contains statistically significant outliers, shown by a p-value of 0.017, which allows for the rejection of the null hypothesis that there are no outliers in the series.

Table 5.76: Dixon Test Summary Statistics - AmtOverdue

Dixon test for outliers / Two-tailed test (AmtOverdue):	
R10 (Observed value)	0.559
R10 (Critical value)	0.192
p-value (Two-tailed)	< 0.0001
alpha	0.05

Source: R Script Output

The result (Table 5.76) shows AmtOverdue has a significant presence of outliers, as shown by a p-value of almost zero. Thus, we reject the null hypothesis and conclude that the series has outliers.

Table 5.77: Dixon Test Summary Statistics Rating

Rating	G	G (Critical value)	p-value	Step
5.600	0.208	0.192	0.033	1

Source: R Script Output

The result (Table 5.77) reflects that rating also has significant presence of outliers as shown and thus, a p-value of 0.033 confirms the rejection of the null hypothesis in support of the alternative that there is a statistically significant presence of outliers.

Table 5.78: Dixon Test for outliers in Tenure Summary Statistics

Term	G	G (Critical value)	p-value	Step
5.000	0.421	0.192	< 0.0001	1

Source: R Script Output

The result (Table 5.78) shows “Tenure” series also shows a significant p-value and the presence of some extreme values can be seen. Thus, we reject the null hypothesis and conclude the data has outliers.

Table 5.79: Dixon Test for IntRate outliers

IntRate	G	G (Critical value)	p-value	Step
0.000	0.000	0.192	< 0.0001	1

Source: R Script Output

The above (Table 5.79) shows a statistically significant p-value which are deemed to be outliers present in the series.

Table 5.80: Age-Company – Dixon Test Summary Statistics

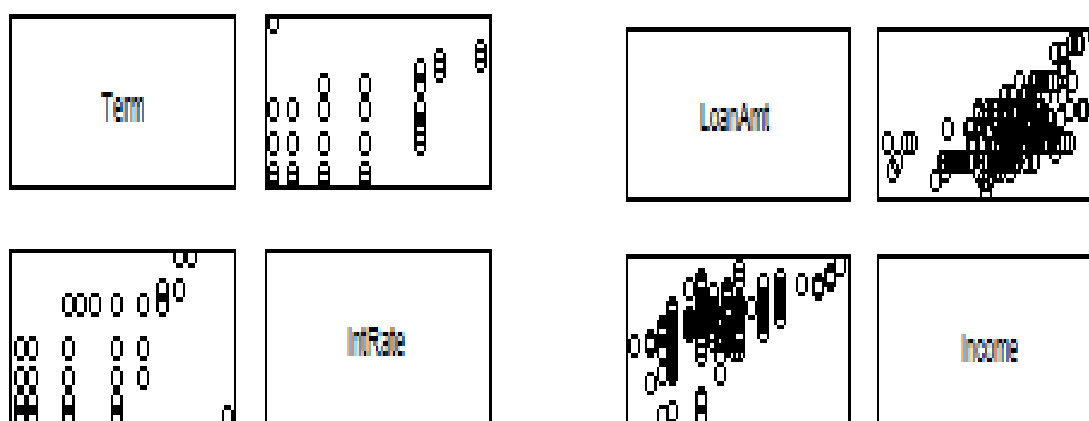
Dixon test for outliers / Two-tailed test (Age):	
R10 (Observed value)	0.023
R10 (Critical value)	0.192
p-value (Two-tailed)	0.562

Source: R Script Output

With a non-significant p-value (0.562) as shown (Table 5.80) above, we conclude Age has no statistically significant presence of outliers, hence, we fail to reject the null hypothesis at five percent level. To fix the outliers in the dataset, logarithmic scaling is applied, where the logarithms of the series with extreme values are taken into the model. After scaling down these series, their new values are plotted in the form of histograms using R's *hist()* function, as shown below:

5.14.5 Testing for Multicollinearity

High standard errors, $SE > 2.0$ on *IntRate*, suggest the possible existence of multicollinearity, which is one of the tests that must be conducted when dealing with regression models. However, formal tests for multicollinearity were conducted, where in one, a visual analysis of correlations among the explanatory variables would be done through a matrixed-scatter plot.

**Figure 5.13: Correlation Scatter Plot Extracts**

Source: R Script Output

From the extracts (Figure 5.13) above, there is some positive correlation between Revenues and LoanAmt and between Tenure and IntRate. This relationship shows

corporates with high revenues/incomes tend to borrow large amounts, as their incomes signal their ability to service their loans, whilst a longer borrowing term tends to attract a risk premium, as the horizon increases, hence, higher interest rates over longer terms.

To further confirm the existence of multicollinearity, high Variance Inflation Factors (VIF) were obtained for LoanAmt, IntRate, Rating and Revenues, signalling the existence of correlations among these variables. Below is a summary (Figure 5.14) of the VIF.

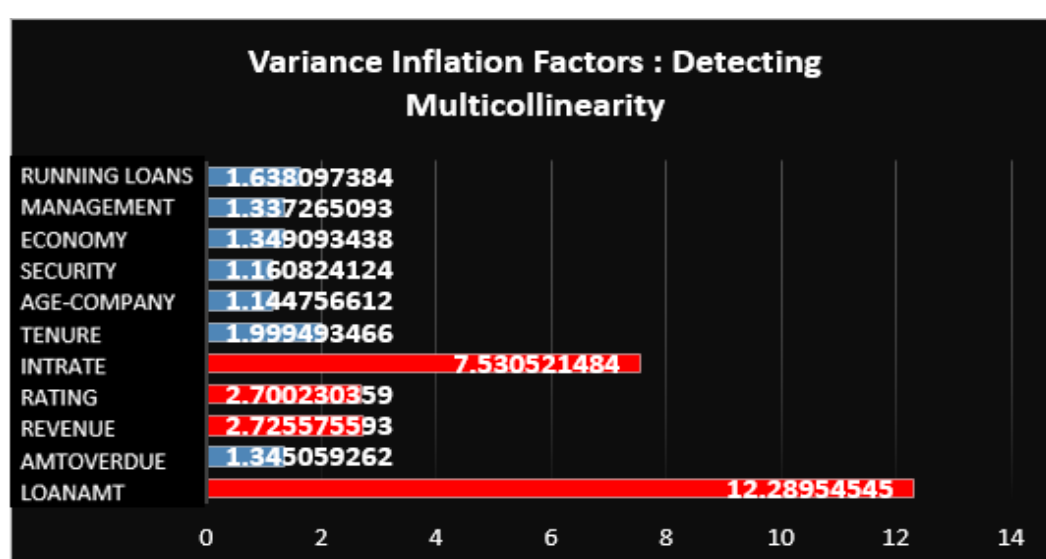


Figure 5.14: Variance Inflation Factors

Source: R Script Output

From this evidence, it is clear multicollinearity is present, since we have obtained VIF values greater than 5.0 (for LoanAmt, Rating and IntRate), which signal the presence of multicollinearity and VIF values closer to three, a value high enough to induce multicollinearity. This means some explanatory variables need to be dropped from the model.

5.14.6 Solving for Multicollinearity

LoanAmt, Revenue, IntRate and LTIRatio have the highest VIF, as such, one variable has to be dropped from the model, whilst attention is paid to the VIF values of the explanatory variables. Income was then dropped. After dropping Income from the

model, LR was fitted and the VIF values of the remaining variables observed and recorded. The chart below (Figure 5.15) shows the VIF figures after fitting the second LR model without Income.

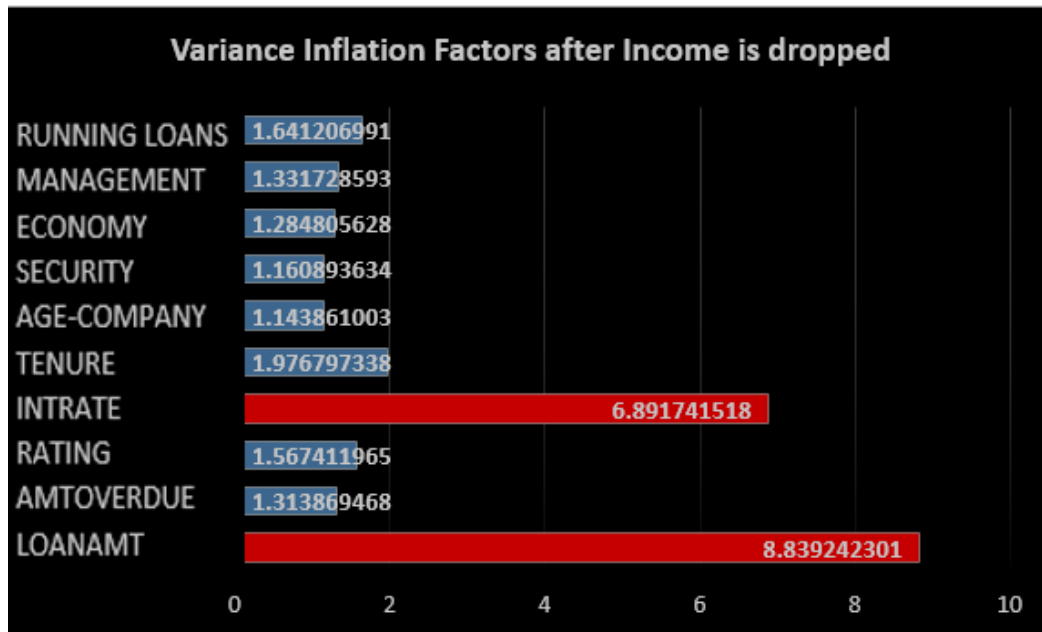


Figure 5.15: Variance Inflation Factors

Source: R Script Output

LoanAmt and IntRate still have very high VIFs (greater than 5.0). In this regard, LoanAmt is dropped and the VIFs are analysed again to check whether there is no more multicollinearity. This is shown in the graph (Figure 5.16) below:

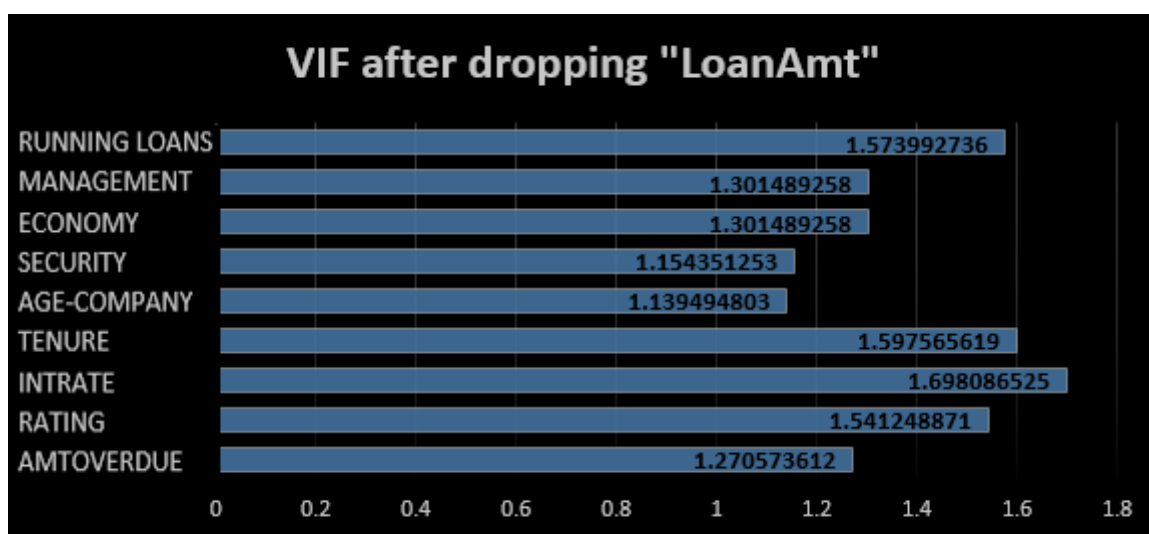


Figure 5.16: Variance Inflation Factors

Source: R Script Output

Now that the VIF values are less than 5.0, we can be sure the model has been cured.

5.14.7 Fitting the Logistic Regression Model

With the model no longer trapped in multicollinearity and without outliers, the LR model is fitted on the training set. Attention is paid to the AIC and the model's residual deviance.

In order to successfully eliminate an insignificant variable from a model, its removal should warrant a significant decline or, in the worst case, no change in the AIC and Residual Deviance figure. Should any of these two metrics increase significantly, the variable cannot be dropped from the model. A summary of the Residual Deviance and AIC values from the model, free from multicollinearity, to the final model capture at every moment a variable is dropped are tabled below (Table 5.81).

Table 5.81: Parameter Selection for Logistic Regression Model

MODEL	AIC	Residual Deviance
Model with all explanatory variables	103.59134	78.59134
Model free from Multi-Collinearity (LoanAmt and Term)	99.977502	79.977502
Dropped Revenue/Income	98.097487	80.097487
Management dropped	94.293469	80.293469
IntRate Dropped	92.326027	80.326027
Running Loans Dropped	90.733504	80.733504
Age-Company Dropped (Model with Significant variables only)	89.53757	81.53757

Source: R Script Output

The summary of AIC and residual deviance above (Table 5.81) shows a LR model that has significant variables is only arrived at through a step-wise reduction process, whereby the residual deviance and AIC are decreasing gradually; by removal of each variable or those with a very small increase. This means only AmtOverdue, Rating, Security and Economy are statistically significant.

5.14.8 Final Credit Score Model

Using R's *glm()* package, the LR model is estimated on the training set and tested on the testing set to see whether the LR test has been successful, as illustrated (Figure 5.17) below.


```

Call:
glm(formula = Default ~ LTRatio + AmtOverdue + Economy, family = "binomial", data = LRtrain)

Deviance Residuals:
    Min       1Q   Median       3Q      Max  -2.2252389
0.2293707 0.3773937 0.5191286 3.0779129

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.80598472  0.67487232  2.67604 0.0074498 **
Rating       0.72752502  0.42181375  1.72475 0.0845718 .
AmtOverdue   -0.07603041  0.02247099 -3.38349 0.0007157 ***
Security     -1.28007806  0.61025291 -2.09762 0.0359388 *
Economy       1.32587612  0.08593469  2.67852 0.0268952 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 124.19993  on 122  degrees of freedom Residual deviance:
82.53757  on 119  degrees of freedom

AIC: 89.53757

Number of Fisher Scoring iterations: 7

```

Figure 5.17: Output 1: Logistic Regression Model

Source: R Script output

In equation form it can be written as follows:

$$Default = \frac{1}{1 + e^{-1.085984 - 0.727525 \log(Rating) + 0.07603041 \log(AmtOverdue) + 1.2800780 Security + 1.32587612 Economy}}$$

From the above formula, the amount a borrower owes in previous debts explains the capacity to service a loan extended to them. It is, therefore, important that borrowers be less indebted. A positive AmtOverdue coefficient implies a positive relationship between AmtOverdue and a borrower's credit quality; AmtOverdue amplifies the risk of defaulting. Security, likewise contributes to whether a firm defaults; when security is available, the chance of default will be low largely due to worthwhile pledged security. The state of the economy also contributes to defaulting or non-defaulting, in that, when the economy is experiencing a depression, defaults are likely and when the economy is experiencing a boom, defaults are less likely. Lastly, previous external ratings are crucial in determining default. When previous ratings are bad, there will be a high chance the client will default.

It can also be concluded that 0.5 is the cut-off probability of potential clients likely not to default. Therefore, when probability to default is: $d > 0.5$, the probability for borrower to default is low. However, when probability to default is: $d < 0.5$, the probability for borrower to default is high and the application is declined.

5.14.9 Goodness of Fit Tests

The LR model was tested for goodness of fit using the Pearson Chi-square test for goodness of fit and Deviance D. The model was tested with all input variables and a p-value of 0.1381 was obtained (Figure 5.18). This probability value was statistically insignificant, implying the model fits well on the data. Thus, we fail to reject the null hypothesis.

The extract below indicates how the test was conducted in R using the *pchisq()* where the first parameter is the difference between the Residual Deviance values, and the second is the difference between the degrees of freedom of both the model with all explanatory variables and the final model.

```
pchisq(82.53757-78.59134,119-111)
[1] 0.1380581189
#Goodness of fit
```

Figure 5.18: Output 2: Pearson Chi-Square Test

Source: R Script output

The Hosmer-Lemeshow test was also conducted using the R-libraries *generalhoslem()* and *ResourceSelection()* packages, concluding the model fits well on the data set, given a statistically insignificant p-value (0.204), with 123 degrees of freedom Chi-squared test (Hosmer-Lemeshow test). Below (Figure 5.19) is a snippet of the R-script result for the Hosmer-Lemeshow goodness of fit test.

```
Hosmer and Lemeshow goodness of fit (GOF) test

data: LRtrain$Default, fitted(FinalModel)
X-squared = 123, df = 8, p-value = 0.204
```

Figure 5.19: Output 3: Hosmer-Lemeshow Test Results

Source: R Script Output

5.14.10 Validation of the Credit Score Model Performance

The performance of the LR model is evaluated on the testing set (the unused 30 percent of the dataset) and from this set; the confusion matrix is constructed; misclassification and accuracy errors (Rates) are calculated from the matrix. The lower the misclassification error, the better the accuracy of the model. A misclassification rate in the testing set lower than in the training set indicates the model is not overfitting, which is the case with the model produced here.

5.14.11 LR Confusion Matrix Analysis

The diagram below (Figure 5.20) shows the confusion matrix for the LR model based on the training set from which the Accuracy and Misclassification errors are computed.

		Predicted	
		0	1
Actual	0	11	14
	1	1	97

Figure 5.20: LR Model Training set Confusion Matrix

Source: R Script Output

Approximately 12.20 percent of the records included in the training set have been incorrectly classified, with 14 incorrectly predicted not to default (11.38 percent) and one incorrectly predicted to default, representing 0.813 percent. This means the model was able to accurately learn and predict defaults with an accuracy rate of 87.80 percent. A cross-validation of the model with the testing set shows the LR model adopted is quite consistent on both the training set and the testing set. The confusion matrix and the misclassification error from the testing set are illustrated (Figure 5.21).

		Predicted	
		0	1
Actual	0	4	5
	1	0	37

Figure 5.21: LR Model Test set Confusion Matrix

Source: R Script Output

The model generalises quite well on the test set, with a misclassification error of 10.87 percent, wholly obtained from defaults classified as non-defaults, with incorrectly predicted non-defaults totalling to non-defaults and nil for defaults. Thus, the LR model generalised new data with 89.13 percent accuracy. The model misclassified only by incorrectly predicting defaults as non-defaults, which is quite disastrous from a credit risk management point of view. The model is quite consistent in both the training and testing datasets.

5.14.12 Model Performance Using the ROC Curve and Area under Curve

The LR ROC curve showed a very high accuracy performance with the curve's area under curve value of 0.888, as shown in the curve below (Figure 5.22). The ROC curve is closer to the left vertical axis, indicating better prediction of defaults. Likewise, where the curve is closer to the upper horizontal curve, it indicates better prediction of non-defaults.

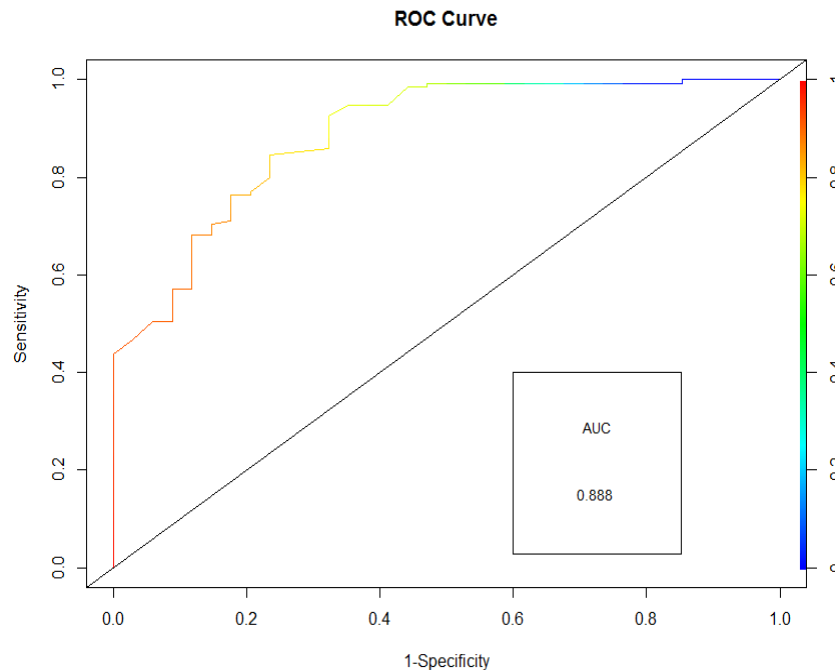


Figure 5.22: LR Model ROC Curve and AUC

The LR model exhibits a very high discriminatory power, performing very well in predicting non-defaults, as shown by the ROC staying close to the upper 1-specificity axis, and defaults, as shown by the ROC curve staying closer to the sensitivity axis. It can, therefore, be concluded this model is a success and can be used by Commercial banks to evaluate corporate loans.

In line with the main research question which is - To what extent and in what manner is loan performance of Zimbabwean Commercial Banks impacted by LPM Models? The new model succinctly reveals NPLs will be significantly reduced when the LPM is accurate, hence, improving loan performance and portfolio quality. The research question - What influences a Commercial Bank to change its loan model or develop a model? - saw the study largely argue that low accuracy and efficiency influences banks to review or completely change or develop a new loan model. The results of the new model closed the gap on loan model effectiveness, as it has demonstrated that only variables with significance should be used in a model with a robust technique, such as LG, validated as the technique in developing a credit-score model. Furthermore, utilisation of an effective loan model strengthens loan portfolio due to performing loans.

5.15 Qualitative Analysis and Findings

This section presents the key findings from the interviews with 24 managers, regarding the current state of loan performance models in Zimbabwe. The audio data collected from the interviews with the managers had to first be transcribed verbatim (Merriam & Tisdell 2016). To help minimise confirmation bias, Computer-assisted qualitative data analysis software (CAQDAS) was employed, because of qualitative analyses subjectivity. The researcher, more specifically, employed QSR NVivo v1.3. With the study including a phenomenological inquiry to investigate experiences regarding implementation and challenges involved when using loan portfolio models are used, qualitative content analysis was performed.

Both a traditional content analysis approach and an approach of directed content analysis were employed, with the traditional approach making use of code derivation from the data, while content analysis entailed deriving codes from the extant literature, as explained by Bernard (2013) and Flick (2018). Open coding was the first stage of the process of coding, with child nodes extracted in their raw form from the data, as prescribed by Saldaña (2016) and Thorne (2016). Axial coding was then performed, classifying codes into tree nodes, according to their commonalities and relationships (Yin 2018). Last, context-specific inclusion and exclusion criteria were used to filter out aspects beyond the study scope through selective coding (Yin 2018). Appropriate visualisations were made to better illustrate the themes and this included the use of thematic maps, hierarchical charts, word clouds, as well as word trees.

The qualitative analysis comprises six key sections. Assessment of respondent profiles are presented in the first section, while Section A to Section E findings of the interview guide are presented in the second to sixth sections, including findings from each research objective. The themes and sub-themes from the data collected have been presented, analysed and interpreted in these sections, with the last section providing a summary.

5.15.1 Respondent Profiles

Known to be subjective in nature, qualitative studies thus present challenges regarding the findings being trustworthy. Nonetheless, two strategies were used in order to ensure the trustworthiness aspect would be guaranteed. The researcher first selected

participants purposively, ensuring they had ample risk management experience, mainly senior risk officers, as well as the management of loans (Merriam & Tisdell 2016). It was against these parameters that professionals were purposively selected to participate in the research study; according to their exposure to and active senior roles in risk management. This type of an approach, according to Marshall and Rossman (2014) and Merriam and Tisdell (2016), ensured the findings of the study would be based on sources that are well-informed and trustworthy, thereby strengthening the findings' credibility.

Second, their feedback was analysed for potential bias that could potentially influence the trustworthiness of the findings, with sources examined through cluster analysis through similarity of words done in NVivo, using the Sorensen–Dice similarity coefficient, as prescribed by Bernard, Wutich and Ryan (2017) as well as O'Neill, Booth and Lamb (2018), with linkages presented in the cluster dendrogram (Figure 6.12). Pseudonyms were used in participant identification, for ethical reasons, and were labelled SRO 1-14 respectively, for the Senior Risk Officers of active banks and Closed Bank, with SR01-10 for the Senior Risk Officers of closed banks. The resultant classification map is illustrated (Figure 5.23) below.

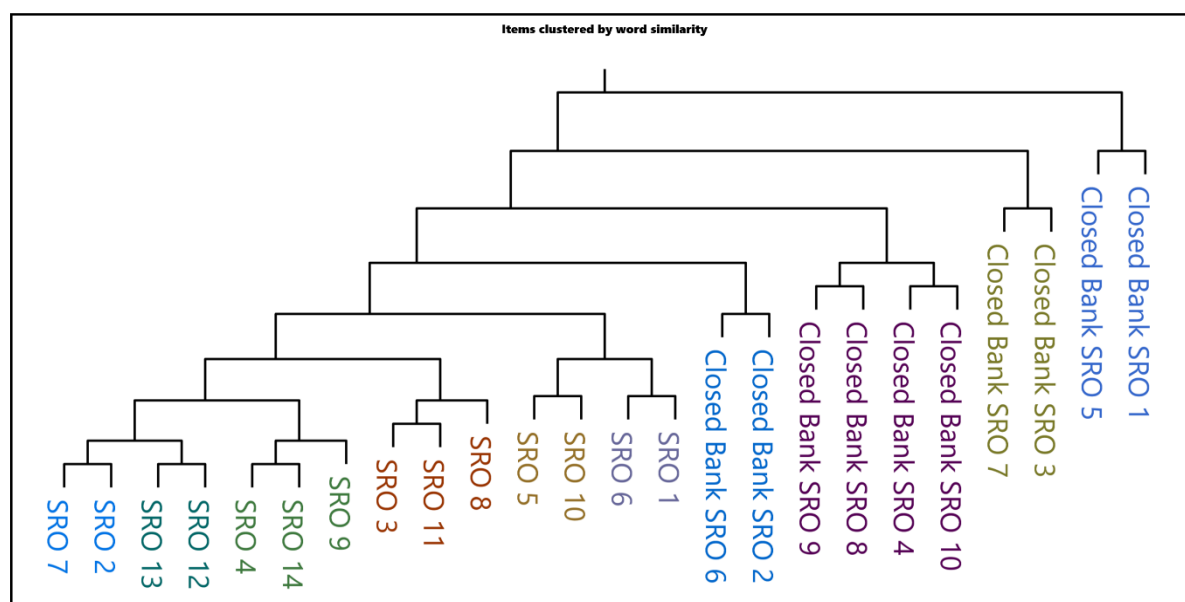


Figure 5.23: Cluster Dendrogram - Interview Similarity Index

The results (Figure 5.23) show the feedback from participants could be ordered into two main classifications; the feedback from the Senior Risk Officers of closed banks

as well as the Senior Risk Officers of non-closed banks. Further similarity in the feedback among the closed banks was grouped into four different groups, while for the operating banks there were three different sub-groups. From these findings, a marked difference is evident in the responses by the SROs from existing and closed banks, implying some polarisation in the feedback from existing SROs and past SROs. This lack of coherence could be due to the four SROs from the closed banks responding from the perspective of the triggers of bank closure, while the input from the existing banks could explain the observed linkages between the existing banks.

The results, therefore, generally confirm some internal consistency regarding the qualitative data used for the analysis and that the trustworthiness of the results could be confirmed with common themes across all responses from the Senior Risk Officers of closed banks, as well as Senior Risk Officers of the running banks. A further break-down of the respondent profiles is presented (Figure 5.24) below.

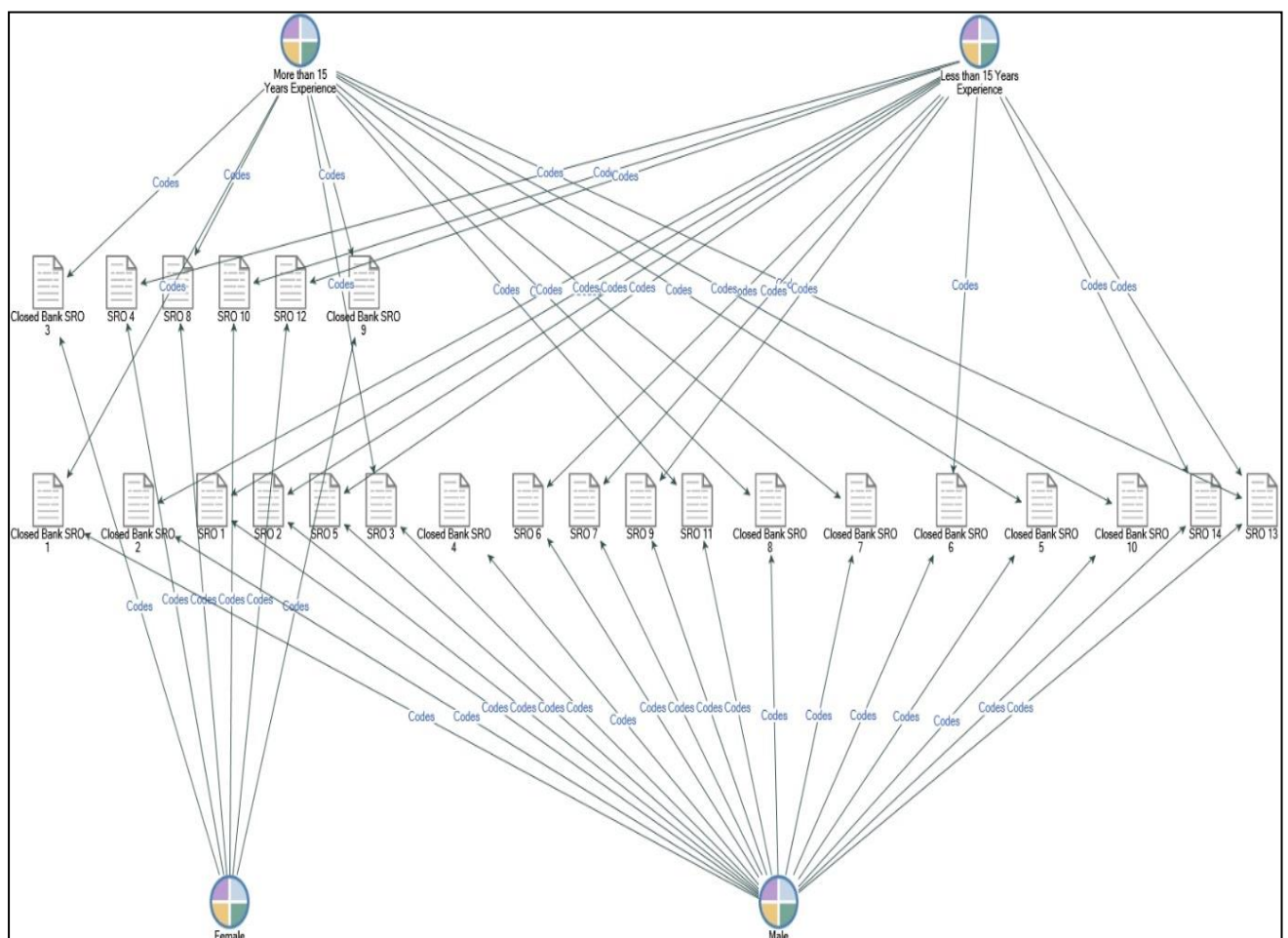


Figure 5.24: Respondent Profile Breakdown

Overall, the study comprised mainly male Senior Risk Officials then females, which is consistent with the general proportions of females in senior positions within the banking sector. ZIMSTAT (2016) noted this to be 28 percent, and the consistency with the current study shows no bias regarding the purposively selected participants. Furthermore, the majority of participants had more than 15 years of experience, adding to the trustworthiness of the findings, as participants had enough experience and knowledge with regard to banking operations.

5.15.2 Section A: Existence and application of Loan Portfolio management models

A general profile of loan models used was examined, with this section presenting the overall profile of the banks and will cover: the models used by the bank; the economic sector where the model was used; the success rate of the model in predicting loan performance; and factors considered in developing a model, as well as the predictive power of each factor. Furthermore, for the qualitative aspects, thematic analysis was carried out in line with a study by Yin (2018).

i. Model Used in the Bank

Participants were asked about the type of model the bank mainly used, out of seven options, namely Internal Credit Score, Asset-Based Model, Z-Score Model, 5 Score Model, Zmijewski Probit Score, Ohlson O-Score, the Odom and Sharda 1990 Model and any other available model under use. The results from the thematic analysis are presented (Figure 5.25) below.

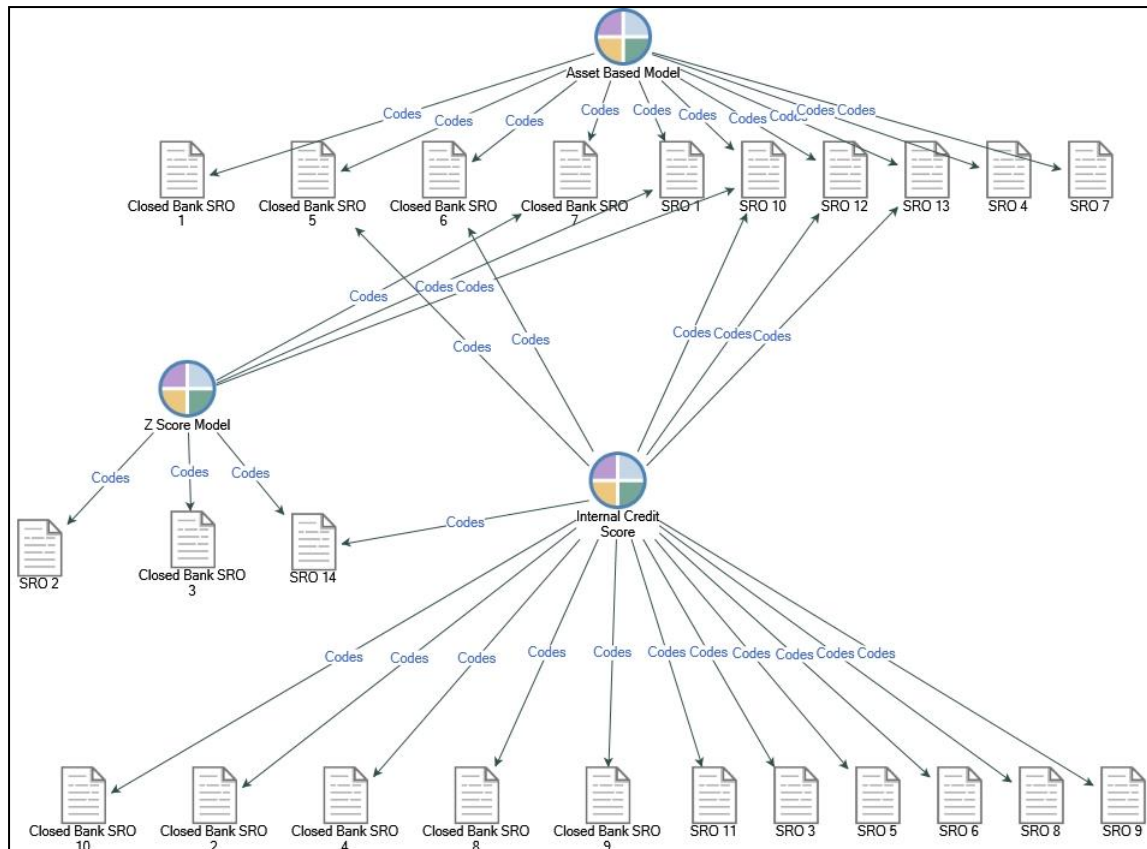


Figure 5.25: Thematic Map - Models used in the Bank

From the outcome, most banks were found to be using the Internal Credit Score Model, characterized by 10 of the current banks as well as seven of the closed banks. The second dominant models were the Asset-based Model as well as the Z-score model, both characterised by six banks; however, the Asset-B Model was characterised by six of the existing banks and four closed banks, while the Z-Score model was also characterised by four of the existing banks and two closed banks. Therefore, of the seven models listed, only three were selected as the main models in use, that is, the Internal Credit Score, Asset-Based Model and Z-Score Model. The other four models were not mentioned by participants as the main models, that is, the 5C Score Model, Zmijewski Probit Score, Ohlson O-Score as well as the Odom and the Sharda 1990 Model. The study, therefore, argues that commercial banks utilise loan models and the most outstanding one is internal credit score, hence, addressing research sub-question i.

ii. Economic Sector where Model was used

Participants were also asked to list the economic sectors where the models were used. To evaluate this, a word cloud analysis was carried out on the listed sectors, where the results show the most dominant sectors as presented (Figure 5.26) below.



Figure 5.26: Word Cloud - Economic Sector where Model was used

The results show the majority of participants mentioned manufacturing as the main sector where the model was being used, followed by the mining sector, then the retail sector, transport sector, and engineering sector, as well as the agriculture sector. Other sectors were mentioned, but were, however, not dominant. It can be argued that the outstanding internal credit score model is applicable to most sectors.

iii. Success Rate of Model

The third section examined the success rate of the model in predicting loan performance, and to achieve this, participants were asked to rate on a 4-point Likert scale for the success rate bands 0-25, 26-50, 51-75 percent as well as 76-100 percent. Responses were again coded into NVivo and the corresponding results (Figure 5.27) presented.

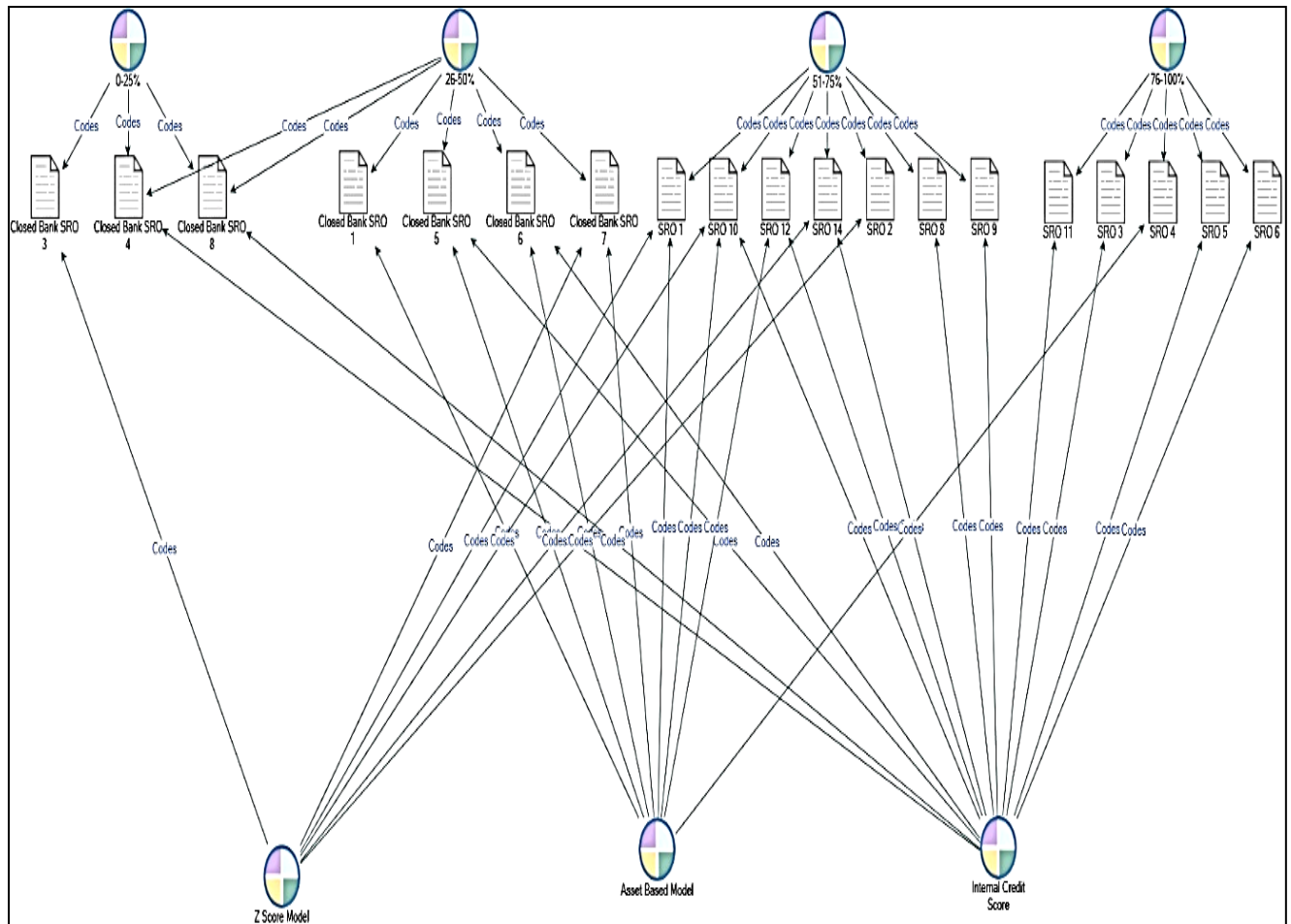


Figure 5.27: Thematic Map - Success Rate of Model

The above results (Figure 5.27) show the Internal Credit Score model was generally associated with high success rates with five mentions having a success rate between 51-75 percent, and four between 76-100 percent, another two between 26-50 percent by a closed bank, and the last two between 0-25 percent by a closed bank. Thus, for rating by all operational banks, the Internal Credit Score model was rated as having more than 50 percent accuracy in predicting loan performance. Nevertheless, the Asset-Based Model had three ratings between 51-75 percent and one between 76-100 percent, with these all rated mainly by operational banks. It can be argued the high success rate of a loan model will cover the gap of not knowing what tool a bank should use in the future, also addressing accuracy matters (research sub-question i).

Four of the ratings were, however, less than 50 percent and these were by closed banks, where the accuracy of the Asset-Based Model was rated as between 0-25 percent. The Z-score model was generally associated as relatively moderate, with only four of its mentions having an accuracy of 51-75 percent by operational banks,

while one closed bank rated its accuracy as between 26-50 percent, with the other rating, also between 26-50 percent, was from a closed bank. Overall, the results show that among operational banks, the accuracy rates of the models, en masse, was generally high, being rated above 50 percent accuracy, while for the closed banks, these accuracy rates were generally lower than 50 percent. Most importantly, the results show that among all the models used in the bank, the one with a predominantly high accuracy was the Internal Credit Score model.

iv. Factors Considered in Developing a Model

The above sub-sections explored the models used and their respective success rates, nonetheless, the study further sought to establish the key factors considered in developing the models. The summary of the findings is presented in the hierarchy chart below (Figure 5.28).



Figure 5.28: Hierarchy Chart - Factors Considered in Developing a Model

A total of eight themes was extracted from the analysis. However, the most prominent theme considered was inflation; identified as the main factor by almost all participants. One of the participants, SRO4, outlined clearly that:

“The Zimbabwean macro-economic situation has been characterized by a high inflation volatility, particularly before 2009, as well as periods after 2018 when the country adopted the local currency, phasing out the multi-currency regime. The fact that these periods have been characterized by hyperinflation makes the aspect of inflation a key factor that we consider when creating the loan models. Yes, in other countries, the inflation is factored in, but it is not a prominent factor as it is in Zimbabwe as well as other hyperinflationary countries such as Venezuela. As we speak, the inflation rate for Zimbabwe remains a double figure, above 50%, and this makes it a huge concern and hence the need to consider it as the main factor to minimize the losses that could be incurred mainly from long-term loans.

Other factors mentioned by participants were risk exposure, GDP, efficiency of the loan model, and the economic sector of the loan applicant, as well as age of loan applicant, the collateral provided by the loan applicant, and the age of the account. Following axial coding, or the coding of factors with common themes, three key factors emerged namely, macro-economic factors, personal factors and model factors. The thematic map illustrating these findings is presented (Figure 5.29) below.

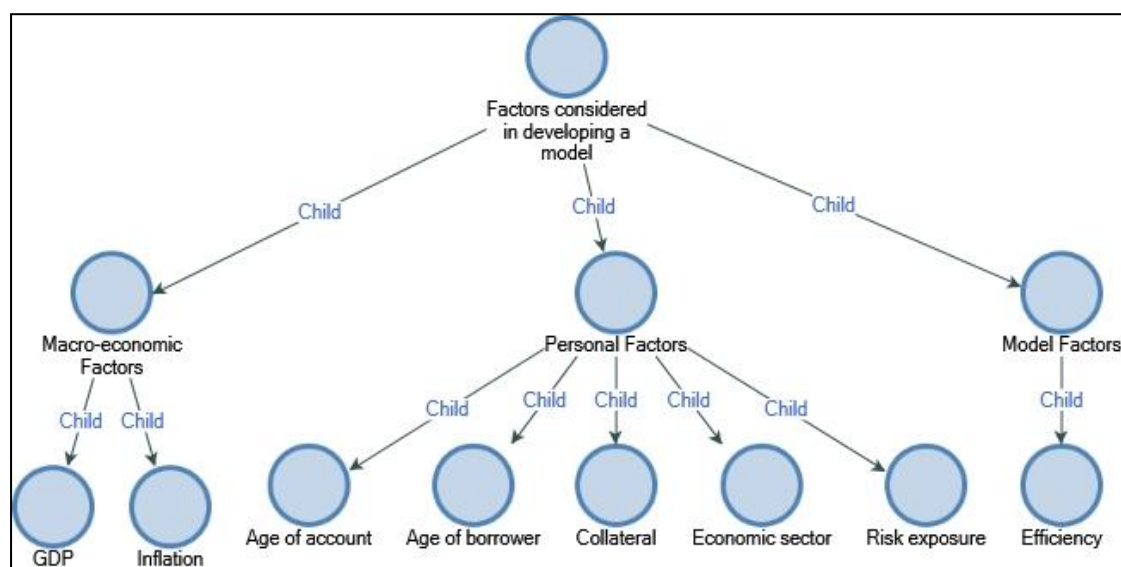


Figure 5.29: Thematic Map – Reclassified Factors Considered in Developing a Model

The results show that among the macro-economic factors considered in developing the model were inflation, as well as GDP. Personal factors included the age of the

borrower's account, age of borrower, collateral by borrower, and economic sector of borrower, as well as the risk exposure of the borrower. Last were the model factors and the only listed attribute considered thereunder was model efficiency. It can therefore be concluded that economic outlook is key in any loan model.

v. Predictive Power of Each Factor

Participants were further asked to establish the predictive power of each factor considered in developing loan models. This question was structured where one represented low and five represented a high predictive power. The factors were reclassified according to the modal number of participant classifications and the result is illustrated (Figure 5.30) below.

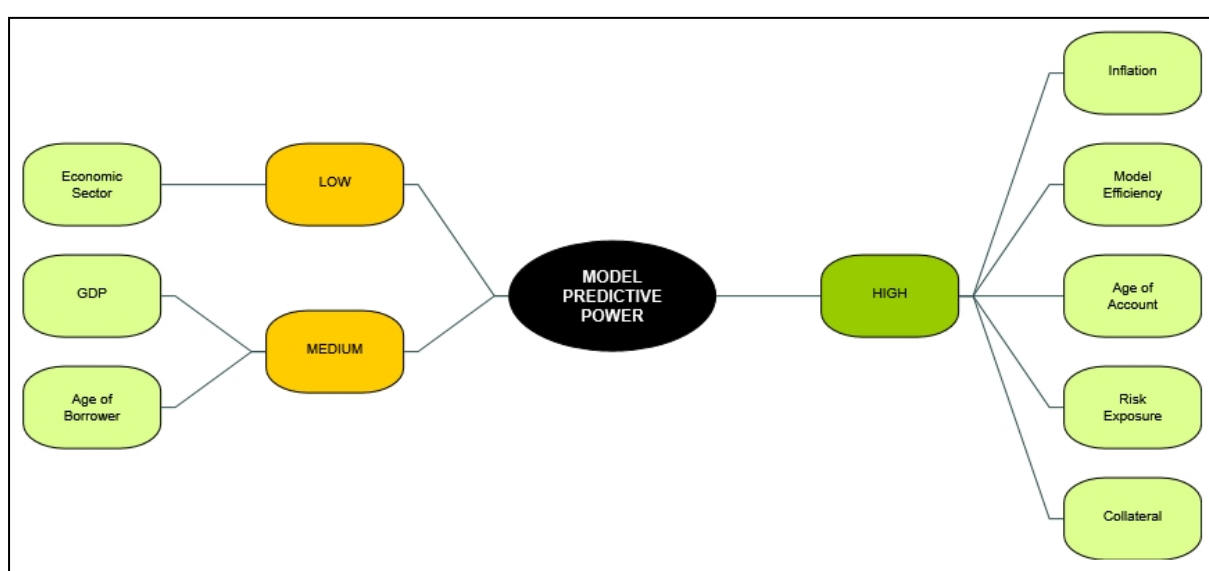


Figure 5.30: Model Predictive Power Classification

According to participant classifications, five of the eight factors were considered as having a high predictive power (most frequently rated as four or five), namely; inflation, model efficiency, age of account, and risk exposure, as well as collateral. Nevertheless, two were dominantly coded as having a medium predictive power (most frequently rated as three); these are GDP and the age of borrower. Only one factor was rated as having a low predictive power (most frequently rated as one or two), namely the economic sector of the borrower.

vi. Determining Loan Model Efficiency

The last aspect of the first objective was to establish the means used by the non-operational banks to determine loan model efficiency prior to collapse. Several themes emerged (Figure 5.31) but the most prominent was consideration of the NPL level, as shown below.

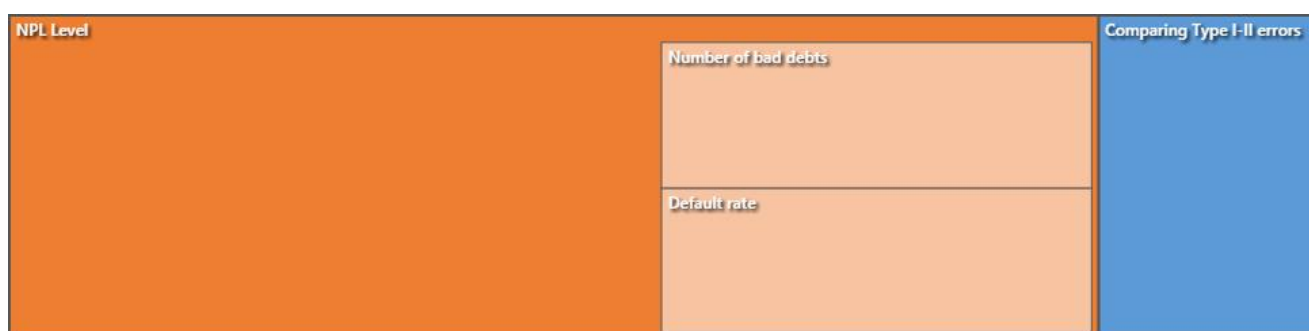


Figure 5.31: Hierarchical Chart: Determining Loan Model Efficiency

Following axial coding, the NPL level was also considered a super-node to the number of bad debts, as well as the default rate. The second separate theme extracted was the comparison of the Type i and Type ii errors. These findings were confirmed by Closed Banks, for example, SRO4 stated:

Essentially, the efficiency of the loan models was mainly evaluated against a prescribed or tolerable NPL threshold. Under normal circumstances, globally, the NPL ratio is supposed to be less than 5%, but the Zimbabwean situation is a big different as the operating environment is somewhat harsh and abrupt policy changes often have a huge effect on the NPL. At the time our bank was functional, we used the default rate as the key determinant of the efficiency of the loan model. Our bank had set a maximum of 10%, but due to regulatory pressure and mainly the poor economic climate, the NPL often exceeded 10% and this prompted us to revisit the model and adjust to suit the changing political, and socio-economic situation in the country.

Based on the above, the major determinant of loan model efficiency can be confirmed as the NPL ratio or rather, the default rate. However, this work has argued that the country has some specific loans models (credit score, asset based and z score) under use to predict loan performance hence their full optimization may reduce NPLs.

5.15.3 Section B: Model Parameter Attributes

Characteristics of an Effective Loan Model were brought to the fore following evaluation of loan model attributes. Thematic coding was again conducted using NVivo, and the five key themes extracted are illustrated below (Figure 5.32).

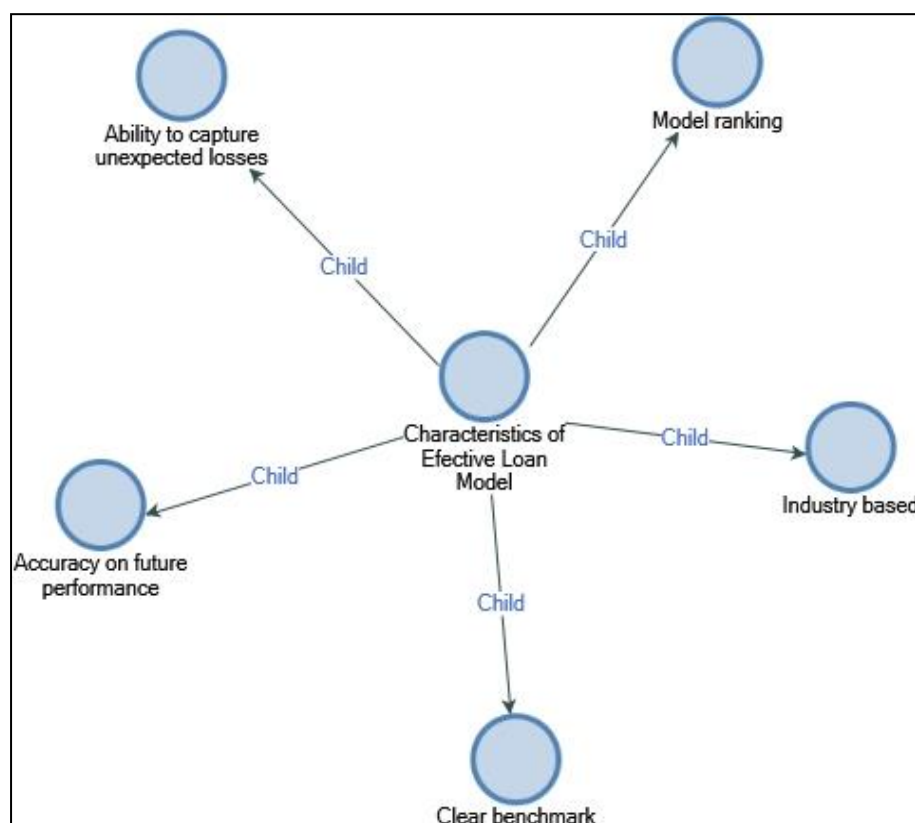


Figure 5.32: Thematic Map - Characteristics of an Effective Loan Model

The results show the five key characteristics or parameters of an effective loan model comprised a model being able to capture unexpected losses, a model that allows for ranking, an industry-based model, a model with clear benchmarks, as well as a model that can predict future performance with accuracy. Regarding the ability to capture unexpected losses, SRO5 said:

The Zimbabwean economy has greatly been characterized by arbitrary policy changes and this affects business, mainly, the banking sector. A case in point is various Statutory Instruments which are introduced with no notice and banks are greatly affected by these directives. To mitigate the potential losses that are often accompanied by unexpected changes in the regulatory

environment, it is vital that any loan performance model that shall be used by the bank should be able to factor unexpected losses.

This was reiterated by SRO9, who added more information, but stressed the need for a model that remains accurate regarding future performance:

Models that should be adopted should not be short-term, but should remain accurate for a protracted period given that the banks offer loans and mortgages that span as far ahead as 25 years. The loan model would be able to generate a near-accurate amortization schedule that remains resilient to macro-economic environment, political shocks and other natural hazard shocks such as pandemics. Therefore, having a loan portfolio model that remains accurate over protracted periods is very important.

The other key theme dominant among the participants was the need to have industry-specific models, as argued by Closed Bank SRO3, who said:

One of the drawbacks of our bank before it collapsed was that we used to apply one loan model across different sectors, and this had devastating consequences. The performance of businesses differs greatly across different sectors. Therefore, loan models should not be a one-size-fits-all, but should be adjusted to suit specific industries. A case in point, while climatic shocks may affect agricultural production and increase the risk of defaulting, this may not be the case for other sectors such as retail or education. In this regard, developing a loan model should be tailor-made and customized to suit the key variables that might influence the performance of specific industries/sectors, and by doing so, this improves the efficacy of the models.

The study, therefore, argued well on all parameter attributes alluded to above satisfactorily addressing sub-research question ii (parameter attributes) and this also suggests a loan model guided by best parameters is likely to be effective, hence, low NPLs; thus, further addressing the main research question.

5.15.4 Section C: Effectiveness of Loan Portfolio Management Models

This third section was aimed at evaluating the key factors that significantly impact the effectiveness of LPMM on loans. To achieve this, a PESTLE analysis was carried out, comprised of the Political, Economic, Social, and Technological, as well as Legal Environment, along with the Internal Environment factors. The overall comparison across all these factors is presented (Figure 5.33).

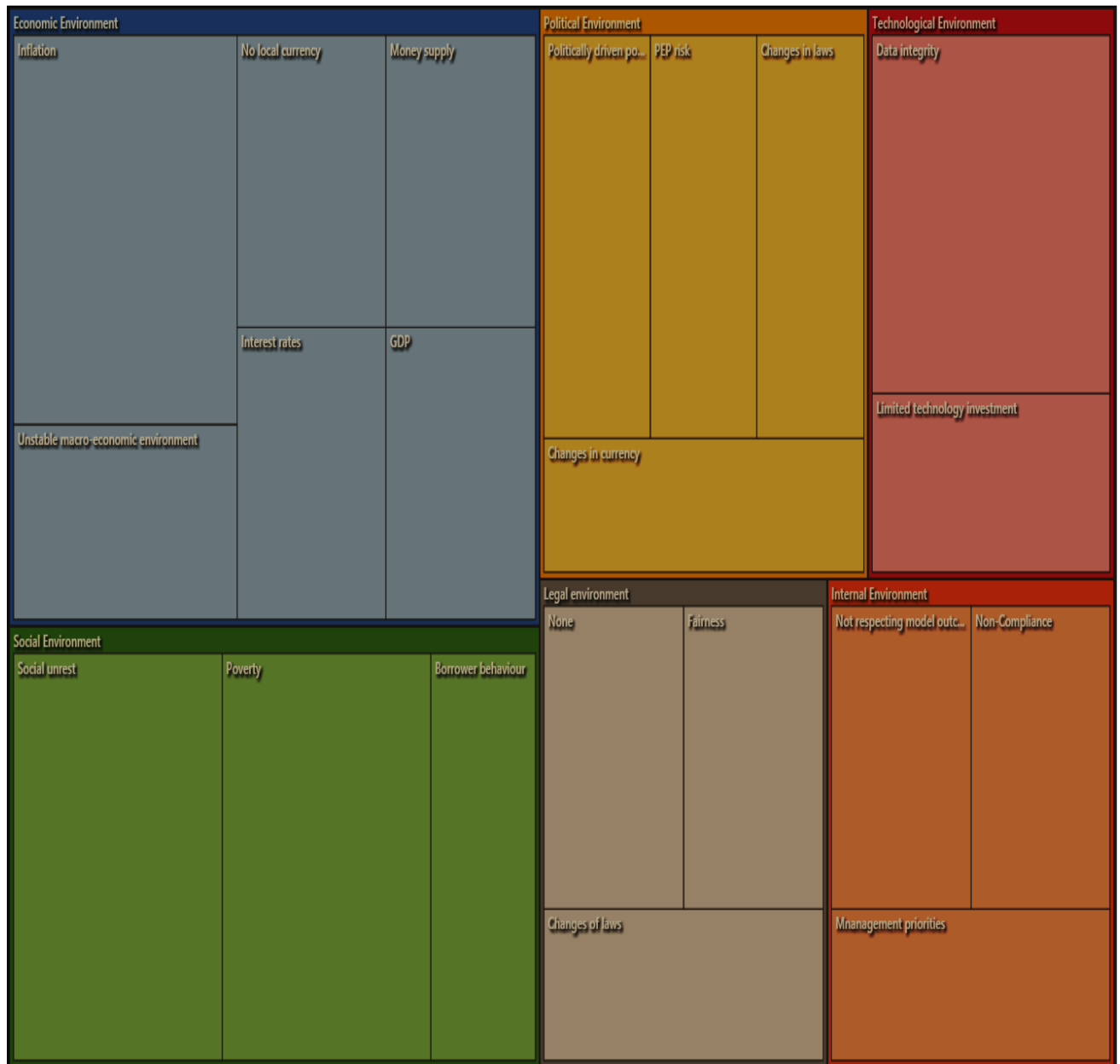


Figure 5.33: Hierarchical Chart - Factors Affecting Effectiveness of LPM

The hierarchical chart above shows 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, with the legal environment, internal environment, as well as the technological environment also dominant.

i. Economic Environment

From Figure 5.33, 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, then interest rates, poor money supply, as well as the country's GDP. Inflation was reinforced by SRO6, 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 affects the efficacy of the loan portfolio management models.

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

ii. Social Environment

Regarding the social environment, three sub-themes were extracted which included social unrests, 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 SRO10 highlighted:

The likelihood of defaulting 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 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 the poor loan portfolio management model performance.

Borrower behaviour was also presented as a key driver of loan defaulting 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 defaulting.

iii. 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 political risk was a key factor negatively affecting the LPMM performance and a key contribution was provided by SR02:

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 characterized by the further devaluation of the newly adopted local currency in 2018, which economists consider as implemented pre-maturely without the necessary macro-economic 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 LPMs.

iv Legal Environment

On 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. SR09 highlighted:

"The legal environment plays a key role in influencing loan default rates. There are several examples that can be drawn from past experiences, but most importantly, are 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.

v. Internal Environment

The internal factors in the bank were also mentioned as having a significant influence on the effectiveness of LPMs. The main theme that emerged was management non-compliance, as also evidenced by the sub-themes "not respecting model outcomes" and "management priorities". This was also corroborated by one of the closed bank participants, Closed Bank SR01 who argued:

One of the challenges that we faced prior to the collapse of the bank was the failure by the management to respond timely to the model outcomes, but rather reverting to impulse-driven decisions in lieu 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.

Regarding the internal environment, management therefore played a key role.

vi. Technological Environment

The last factor was the technological environment and from the outcome, there were two key sub-themes extracted, namely data integrity, as well as limited technology investment by the banks. One of the participants who explained this well, was SRO11:

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 skill 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 that can manage the training of the models as well as their deployment. Most importantly, it 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, robustness of the available systems for the modelling, as well as the technical expertise available. It can therefore be concluded that commercial banks measure effectiveness of loan models by reviewing its capacity in evaluating the environment fully. Thus means this section addressed sub research iii adequately.

5.15.5 Section D: Reasons for Bank Failure

The fourth section examined the key reasons for bank failure. From the evaluation of participant input six factors were extracted, including corporate governance issues, the lack of disaster recovery mechanisms, management complacency, and the use of outdated models, as well as poor markets and poor planning. These themes are illustrated (Figure 5.34) below.

Generally, these factors do corroborate the PESTLE factors examined in the preceding section, however, this puts more blame on the internal environment. Three of the six factors were due to the internal environment and these include: corporate governance issues, management complacency, as well as poor planning. Furthermore, the use of outdated models and the lack of disaster recovery was largely related to the technological environment, while the last factor, poor markets, was largely as a result of the poor social and economic environment.

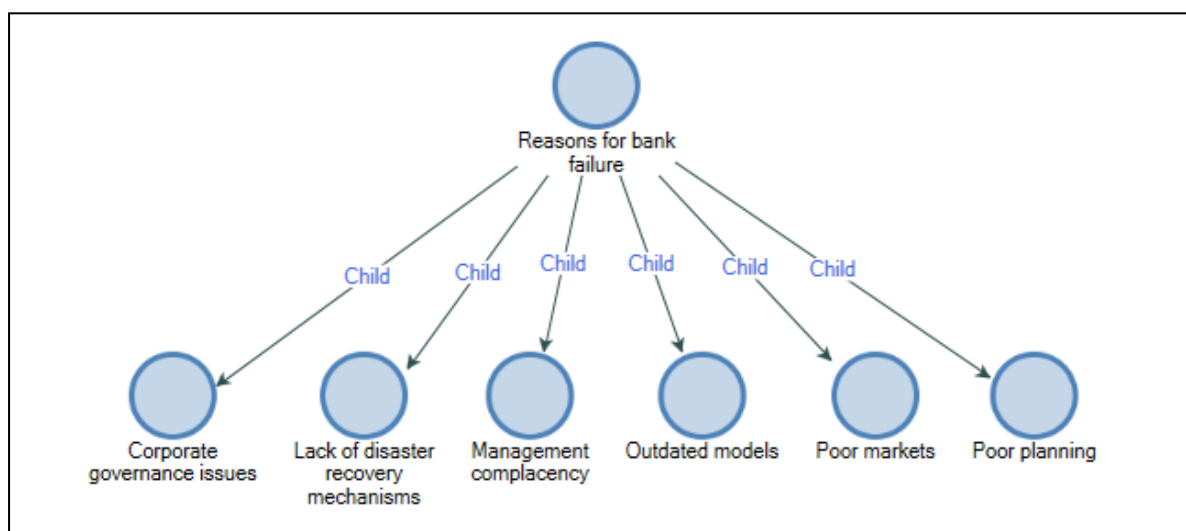


Figure 5.34: Thematic Map - Reasons for Bank Failure

While it is widely accepted that corporate governance issues were among the reasons behind the fall of most Zimbabwean banks, such as Time Bank, Barbican Bank and Royal Bank, other factors were also cited; particularly management complacency and the use of outdated models, which collectively affected the ability by the bank to respond on time. SRO1 affirms:

It's all about what action the management takes when the numbers speak something, unfortunately management ignored the meaning of the numbers.

This also corroborates the theme found in the previous section, where the sub-themes “not respecting model outcomes” and “management priorities” were discussed, thereby further justifying the importance that management heed key insights that emerge from the modelling techniques, as they offer timely alerts and triggers that can help avert a financial crisis on time. However, at the time in the 2000s, the banks had limited modelling techniques, tools and human capital that are widely available today. Further, SR08 noted:

Owing to the increased uncertainty of the business environment, especially unforeseen circumstances such as pandemics or war, it is imperative that the loan models remain up-to-date, as the use of defunct models is behind is often associated with an increased credit risk for the banks, which potentially affects the loan performance.

Some former bankers reiterated that the quality of clients also played a critical role in bank survival and noted that bigger multinational and listed companies preferred to bank with international banks hence supporting the bank's liquidity position and soundness. Research sub question it was addressed as follows; the study confirms that, notwithstanding use of loan models and their influence at evaluation stage in identifying potential bad debts, NPLs do occur due to the following reasons: banks not respecting loan model outcome, banks using outdated models, corporate governance issues. This gap will be closed by new insights on loan model effectiveness as well as new model development.

5.15.6 Section E: To enhance Loan Models

This last section was aimed at evaluating the challenges faced in operationalising the LPMM and how these challenges were mitigated. This will be achieved through evaluation of themes extracted through the use of NVivo, and presented in four sub-sections. The first sub-section presents the necessity of a LPMM in a banking crisis or in a normal environment, while the second presents the constraints experienced in operationalising LPMMs, and the third presents how the bank strengthened its LPMM.

i. Necessity of a Loan Portfolio Management Model

For this subsection, participants were asked why it was necessary to have LPM in a banking crisis or in a normal environment. The results are summarised below (Figure 5.35).

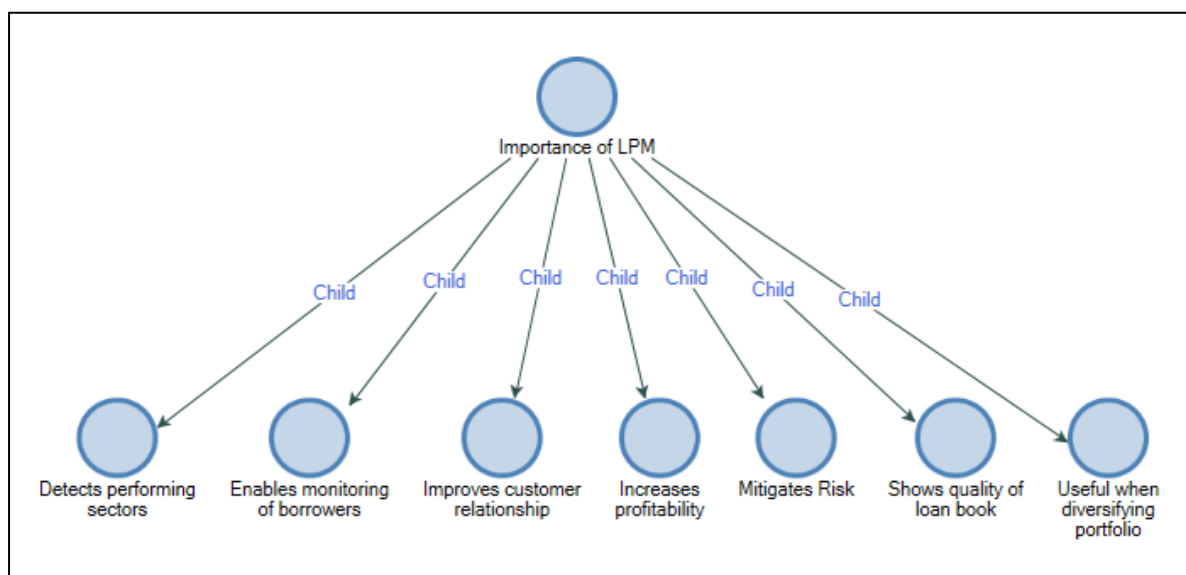


Figure 5.35: Thematic Map - Necessity of a Loan Portfolio Management Model

Seven key themes were extracted and these benefits were that the LPM detects and distinguishes performing sectors from non-performing sectors, enables monitoring of borrowers, improves the customer relationship, and increases profitability, in addition to mitigating risk, showing the quality of the loan book, as well as being useful when diversifying portfolios. Generally, there was consensus among the participants from both closed and operational banks that the LPMM was very important as a risk-mitigation strategy, as well as for improving bank profitability.

ii. Challenges faced in implementing a Loan Portfolio Management Model

The second and most important aspect was to establish constraints experienced in operationalising LPMMs. The key themes are illustrated below (Figure 5.36).

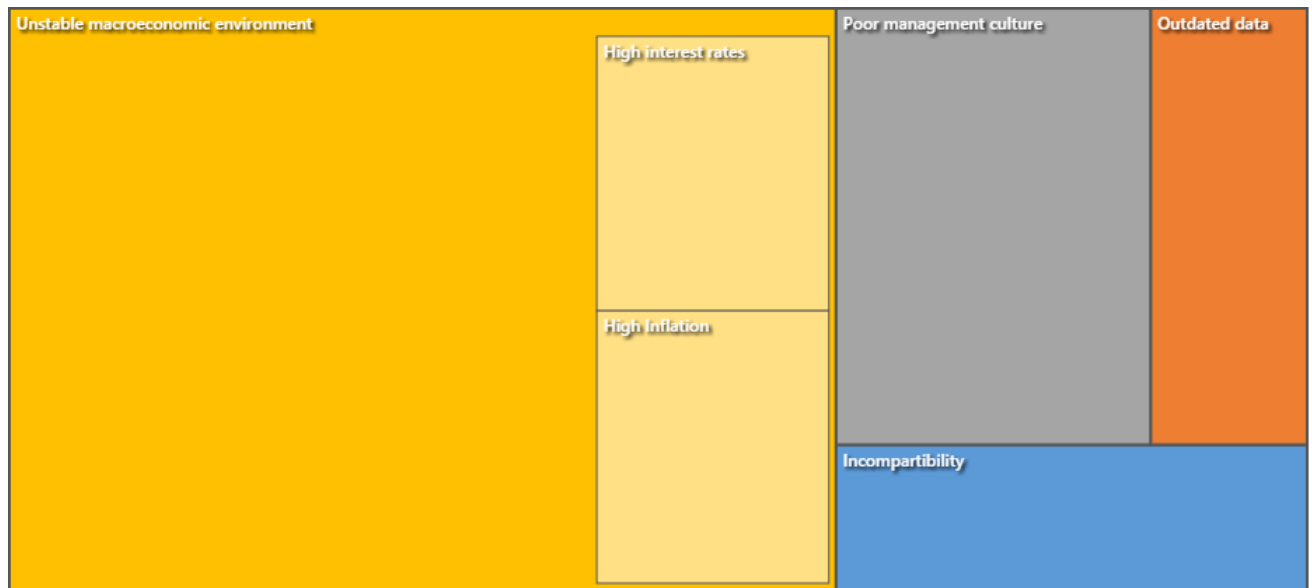


Figure 5.36: Hierarchical Chart - Challenges Faced Implementing LPM

The results show the main challenge faced while implementing the LPMMs was the unstable macro-economic environment. This was characterised by high interest rates and high inflation, which generally corroborates earlier findings that also found inflation and high interest rates as key factors to consider when generating and implementing a LPMM; SRO03 reiterated:

Zimbabwe is somewhat different from other countries where the modelling of LPM tends to be uncertain given the high levels of volatility of both the interest rates as well as the inflation. Other countries with rather stable macro-economic indicators tend to model these LPMs easier and the implementation entails slight modifications from time to time, but for Zimbabwe, hyperinflationary complex LPM approaches have to be employed, which makes the entire process more intricate.

From this narration, participants were clear that the spontaneous and highly volatile hyperinflationary environment is the main cause of concern when deploying the LPMMs, given the complexity of the modelling required to continuously factor in various factors that keep changing under an uncertain and unstable business operating environment. The second factor related to the poor management culture, which also confirms earlier finding on the reasons for bank failure, as well as on the factors affecting effectiveness of LPMMs, where management were also mentioned.

Of key concern is the reliance by some managers on intuitive decisions that are sometimes not backed by data, and as a result, the subsequent LPMMs become ineffective, with their findings sometimes not implemented by management.

The use of outdated data was also cited as one of the challenges. This finding corroborates earlier findings where the high volatility of key macro-economic indicators tends to affect the modelling, given the data used for the modelling keep changing, which entails the need to use more reliable and more current data. However, due to limitations in data warehousing and data architecture systems, some banks resort to the use of outdated data, which will negatively affect model accuracy.

Finally, the issue of incompatibility faced by other challenges is dual pronged. First, it partly relates to the use of outdated data that ultimately result in the creation of incompatible models and second, it relates to the adoption of other models by some banks but sadly, these are not optimised for the Zimbabwean hyperinflationary environment. Consequently, this presents accuracy concerns as the models created will not be compatible with the status quo. Overall, it should be noted that apart from the poor management culture, the other themes extracted do relate to the unstable macroeconomic situation in Zimbabwe, characterised by high inflation and interest rates.

iii How Loan Portfolio Management models were strengthened

The last aspect sought to evaluate how LPM was strengthened, considering the limitations and summary of the findings presented (Figure 5.37) below.

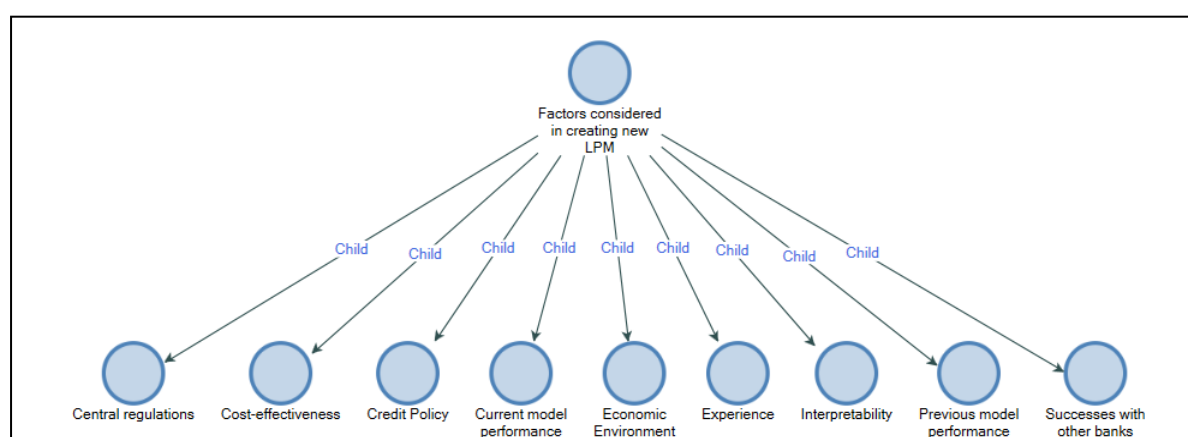


Figure 5.37: Thematic Map - Challenges Faced Implementing LPM

Nine themes were extracted and these included the central bank regulations, cost-effectiveness of the model, credit policy, and current model performance, as well as the macro-economic environment, model history, model interpretability, and previous model performance, along with the successes of the model with other banks.

These findings have shown that when Banks realise that due to various reasons, the model they rely on is no longer effective, they can and will change it. The key driver for such a move has been found in this study to be some environmental factors. Thus, this section fully addressed sub-research question v. The model this study has developed is meant to take care of such leakages.

5.16 Concluding summary

This chapter has presented the study results from the two phases of the sequential explanatory research method adopted for this study. The first phase was quantitative. Analysis of quantitative data was conducted through SPSS v26 as well as IBM SPSS Amos v26 statistical packages. The mean and standard deviations of the data were reported and used to make the necessary inferences, with data accuracy assessed for reliability and validity. Prior to testing the hypothesised relationships, CFA and SEM were conducted to assess the fitness of the measurement and structural models. In addition, the measurement and structural model fitted well. The second, qualitative phase provided insights that helped understand and further cement quantitative results. Thus, the follow-up interviews were very helpful in shedding more light on loan models. To achieve this, thematic analysis was performed to extract the key themes from the data. QSR Nvivo was used as the analytical tool and a total of 24 Senior Risk Officers took part in the study, including 14 participants from existing banks, while the other ten participants were from closed banks. The next chapter presents the key discussions of the study findings, while triangulating with the findings from the quantitative analysis.

CHAPTER SIX

DISCUSSION OF RESULTS

6.1 Introduction

The focal point of this study was to “examine the effectiveness of loan portfolio management models on the performance of commercial banks in Zimbabwe”. This chapter argues and encompasses the discussion of the research results and an elaboration of the inferences from the findings on the loan models. The chapter is organised into four sections, namely: the introduction, data transformation, results discussion and conclusion. It is imperative to discuss the results that would facilitate establishment of the study objectives, as well as contributions. This was achieved by linking the study findings with the related literature on LPMMs.

6.2 Data transformation

The results presented in the previous chapter relate to both the quantitative and qualitative phases of the sequential, explanatory, mixed-methods approach adopted for this study. The results from quantitative data collection were used to inform the qualitative data, as illustrated in Figure 6.1 below.

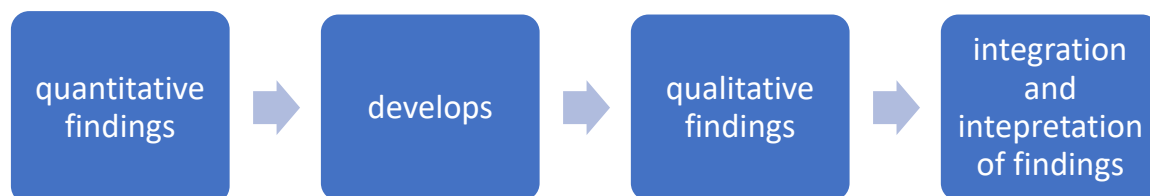


Figure 6.1: Data transformation Steps

The main benefit of this approach, as illustrated by the diagram, was to utilise the qualitative analysis to clarify some findings from the quantitative results, as well as gain more insights from key informants. The two data collection methods, therefore, complemented each other, hence, an enriched appreciation on loan models in the Zimbabwean commercial banks.

6.3 Discussion of results

This discussion is in line with the research objectives and proposed hypotheses. Furthermore, the results are then related to the findings in prior studies.

6.3.1 Objective 1: Existence and application of Loan Portfolio management models

The first objective of this study was to establish whether LPMMs exist and are applied in Commercial Banks in Zimbabwe. In this regard, it was hypothesised that:

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

In addressing the objective, quantitatively, it was dealt with through three aspects, first, the type of loan portfolio model formula used, second, the type of model used and third, the measures of accuracy used. For the type of formulae used, the Score sheet, the ratio, as well as multivariate formula were employed. The most dominant formula used was the multivariate formula, because it was found on almost all loan models used in Zimbabwe, making it first choice when models are developed. Whilst the least dominant formula is the ratio, the loan model may have ratios, but these are a limited variable in the models currently in use.

The findings confirmed that for the relationship between the LPMM and LP, $\beta = 0.616$ ($p = 0.038 < 0.05$). LPMM under use by the Commercial Banks had a statistically significant relationship with loan performance. These results imply the higher the accuracy level of loan prediction performance, the more perceived usefulness of the loan model. In addition, this will also improve the positive attitude regarding the use of loan models toward loan performance in Commercial banks.

With respect to the type of model used, findings from both the quantitative and qualitative analysis indicated the Internal Credit Score, Z-Score, and Asset-Based models were the most favoured models. From the analysis, the most prevalent model was the Internal Credit Scoring model, followed by the Asset-Based model, while the third highest was the Z-Score model. The results confirm banks prefer their own 'home-made' (internal) model, which they tailor-make to suit the business environment and the bank's risk appetite. However, there are also distinctions in

Internal Credit Scoring used for individuals, small enterprise business and corporate clients, largely due to nature of information required and its availability. For example, individuals use salary to pay monthly instalments, whilst corporates use revenues generated from their normal trade receipts.

Findings from the qualitative analysis overwhelmingly supported the results from the quantitative analysis on the significant influence of the Internal Credit score model, which was supported by participants from both operational banks, as well as from closed banks. It is evident from the results that Commercial Banks in Zimbabwe are indeed using loan models as lending tools to evaluate loans at the outset. Therefore, of the seven models listed, only three were selected as the main models used, that is, the Internal Credit Score, Asset-Based and Z-Score Models, while the other four were not mentioned by participants as the main models; these are the 5-Score Model, Zmijewski Probit Score, Ohlson O-Score as well as the Odom and the Sharda 1990 Model.

Once more, the qualitative analysis revealed the majority of the key informants mentioned manufacturing as the main sector where the model was being used, followed by the mining sector, then the retail sector, with other sectors mentioned, but not as dominant. The results show the Internal Credit Score model was generally associated with high success rates between 51-75 percent on operational banks, whilst participants from closed banks discounted the success rate to between 26-50 percent. On the one hand, the Internal Credit Score model was rated as having more than 50 percent accuracy in predicting loan performance for rating by all operational banks. On the other hand, the Asset-Based Model had a moderate success rate from both operational and closed banks.

Key informants from both operational and closed banks revealed five factors considered as having a high level of predictive power (most frequently rated as 4 or 5) and these were: inflation, model efficiency, age of account, and risk exposure, as well as collateral. Whilst factors that had medium-level predictive power included GDP, as well as the age of the borrower. Last, only one factor was rated as having a low level of predictive power, namely the economic sector of the borrower. With regard to the measures of efficiency, both quantitative and qualitative analysis results

reveal the NPL ratio was the greatest indicator, followed by Type i/Type ii errors. These findings were confirmed by both operational, as well as closed bank participants.

The confirmation that the Internal Credit Score is the most dominant model used by banks in Zimbabwe corroborates with among previous studies done in the country (Hlongwane *et al.* 2014; Mutava 2015; Dondo 2019; Matenda *et al.* 2021). It was further confirmed that the loan model is a useful tool in loan evaluation (Hlongwane *et al.* 2014). Loan model level of accuracy (75 percent) was confirmed by Mutava (2015), nevertheless, a deviation from study results, Mavengere (2015) argued that loan models use outdated data, such as financial statements, whilst Dondo (2019) established that loan models cannot be fully utilised in all sectors of the economy. These findings and literature indicate the role of a loan model in credit risk assessment, notwithstanding varying outcomes. However, it confirms that banks are not using judgemental methods to grant loans.

The findings confirm the loan model used has a positive relationship with loan performance. The results are consistent with the financial intermediation theory, which stipulates that key activities of Commercial banks include; brokerage that involves issuance of loans, suggesting quality loans and qualitative asset transformation mainly focusing on credit risk, which applies tools such as loan models, hence, performing loans (Bhattacharya & Thakor 1993). Furthermore, the credit rationing theory used in this study is underpinned by default, interest rate and demand, and is linked to the Internal Credit Score model (Hodgman 1960). This suggests that when a bank does its creditworthiness assessment, it takes cognisance of the three key elements (from credit rationing theory), while approval of client limit demonstrates capacity to service debt and interest, hence, low probability to default or loan performance. This work argues that the credit rationing theory, however, does not specify other key variables that can be applied by a loan model to attain a better accuracy rate.

Meanwhile, portfolio theory (Markowitz 1952) uses risk, return and efficiency, and is linked to the Z-Score model (Altman 1968) in this work. Notwithstanding a positive relationship between loan model and loan performance, the Z-Score has not been

favoured by commercial banks, suggesting elements on theory are not compatible to credit risk analysis. For example, computation of return and efficiency, as well as ratio analysis (Z-Score), do not fully demonstrate client capacity to service debt because of lagging financial statements used, and due to an unstable environment. The theory is also not precise on the sector it should be applied to, contrary to the Z-Score model (manufacturing sector). The obtained results are also linked to lender-based theory (Inderest and Mueller 2007), which aims to reduce credit risk through collateral, hence loan performance, suggesting that whenever a client pledges security, probability of performance is high.

In view of this finding, this study contributes to the current body of knowledge in the Commercial Banks as it has brought new insights regarding the most favoured loan model in a developing nation such as Zimbabwe, namely the Internal Credit Score model, which is based on creditworthiness of clients. A bank should thus utilise a model that can accommodate its mandate, risk appetite, business environment, and targeted clientele base, and which can be enhanced when necessary. This work makes a contribution, in the sense that it provides greater insight into the efficacy of an internationally developed model such as the Z-score. The applicability of the Z-Score in developing nations such as Zimbabwe irrefutably confirmed suggesting they can only be applied in certain business environments, which is key to commercial banks, as they may fail to obtain desirable results from any loan model they adopt. The Z-Score is no longer equally important for banks to use as the sole model when lending, highlighting its shortcomings, particularly on the fact that it only predicts the chances of a business going bankrupt, but does not predict the chances of a business defaulting on a loan.

6.3.2 Objective 2: Model Parameter Attributes

The second objective of this study was to examine the LPM Model parameter attributes currently being used by Commercial Banks in Zimbabwe. It was then hypothesised that:

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

The result was that, for the relationship between the LPMA and LP, $\beta = 0.357$ ($p = 0.046 < 0.05$). Therefore, LPMA under use by the Commercial Banks had a statistically significant relationship with loan performance. These results also imply sound parameters impact performance of a loan model when predicting loan performance at the onset of the application.

Furthermore, the quantitative analysis displayed two components; the first comprised benchmarking attributes, with outcome probabilities, robustness and model outputs being the key terms. The second component related to experience-based attributes. Among the items considered were: the use of industry-based parameters; past loan performance experience; parameters being author-based; and the model incorporating sizeable factors, among others. All these attributes were prevalent as they were all positively rated.

The results additionally reveal setting up of loan model parameters is backed by a number of attributes, among them being industry-based. This means the banks are guided by the regulator, as well as international standards. All parameters used by the banks were positively rated, demonstrating the banks consider a sizeable number of attributes in setting up parameters. Some of the great attributes are; the banks are guided by past loan performance experienced, which means that when previous loans performed well after applying the loan model, it depicted that the probability of parameters being robust was high, hence there is a need to maintain them. Nonetheless, when there are high levels of NPLs, notwithstanding contributory factors, there will be a need to review parameters set in the prior period and improve them, so they can produce better evaluation results going forward.

The least-rated attribute, although it was positive, was “model’s benchmark is well defined”. This suggests the attribute that makes up the acceptable minimum Score is precise. However, in an unstable environment setting parameters with the previous benchmark Scores may not be sustainable. For example, income previously set may not be sufficient to service the loan instalments should they be adjusted upwards due to increase in interest rates in the following year. The study argued that generally in Zimbabwe, for example parameters set in 2016 should be reviewed in the following

year (2017) despite good loan performance, because the macro environment exponentially changes as evidenced by inflation increase (RBZ 2016).

The qualitative analysis shows key informants, especially from closed banks, were of the view there are some parameter attributes that did not influence loan models. Consequently, their loan models could not accurately predict the near future. In addition, an unstable business environment made some of these attributes lag, for example, level of business turnover and or past performance trends were affected by dynamics of the macro environment. Therefore, key informants were of the view that for these parameter attributes to remain relevant and for a loan portfolio model to remain accurate over protracted periods, there is need for consistency and constant reviews.

The qualitative results, furthermore, revealed that neither operational nor closed bank participants found any good reason to review parameters when the loan model performance is robust. However, they emphasised the parameters should assist the bank in computing a loan model benchmark and ranking loan model output. Some key characteristics of an effective model highlighted those attributed to parameter attributes that include; ability to capture losses in the tail events/unexpected losses, industry-based, ranked, with clear benchmark, and accuracy on future performance.

Rosch and Scheule (2007), as well as Markov *et al.* (2022) state, in conformity to Basel ii, lending institutions establish parameters that enable loan models to be objective and effective when evaluating borrowing clients. Nevertheless, Hildebrandt and Gutwirth (2008) observed that an external Credit Score model can assist the bank in developing their own internal parameters for the banks' model. The study argued that there is need to apply the latest data on loan performance, suggesting that, in developing a loan model, the bank is guided by prior parameters that either enhanced loan performance or raised high NPL levels, which can be moderated for the better.

The findings are in contrast with Zhao *et al.* (2015), who determined loan performance prediction was attributed to hidden units. Additionally, Credit scoring models that can be updated with new data could be vital when pursuing higher

predicting accuracies (Dastile *et al.* 2020). In a different dimension, Niu, Liu and Zhang (2020) argued an online credit scoring model improves loan model performance on account of its capability to simultaneously assimilate information on both categorical and numerical features. Furthermore, the results show an updatable model is better than non-updatable models; hence, the need to use newly-generated data to dynamically update the model online to correct model deviation. In line with other literature in this area, the study findings lead to the conclusion that, even though other factors may exist that enhance loan model performance, parameter attributes remain key.

Notwithstanding findings of the study exhibiting the influential role of loan model parameter attributes on loan performance, this work argues that financial intermediation theory is silent on how banks perform brokerage services such as issuance, which involve the initiation of a loan to borrower, and qualitative asset transformation, which is largely credit risk that aims to mitigate default may develop credit tools. Furthermore, the following theories credit rationing, portfolio and lender theory, were used in the study and are reserved on the specific parameters suitable for both a developing and a developed nation with regard to loan model development.

6.3.3 Objective 3: Effectiveness of Loan Portfolio Management Models

The third study objective aimed to analyse LPMM effectiveness and loan performance in Zimbabwean Commercial Banks. In this regard, it was hypothesised that:

H₃: Loan model effectiveness impacts loan performance.

The results show that for the relationship between LME and LP, $\beta = 0.736$ ($p = 0.000 < 0.05$), thus, 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 objective was thus two-fold. First, it was to establish aspects that demonstrate an effective loan model and second, loan performance.

Quantitative analysis implored 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; to identify good clients; to ensure security adequacy; and to compare performing loans to the total asset book, as well as to predict bankruptcy. The second component comprised only two items, deemed reactive measures, because they are applied on an existing loan, determine regular review of security, and suggest measures to be taken when a loan is in doubt.

Items shown to be high-ranking in demonstrating effectiveness of a 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 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 objective further sought to determine loan performance, with results showing some NPLs attributed to various reasons, such as being 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, there are some unforeseen circumstances that cannot be determined by a loan model; such as future markets of the borrower and when upset, clients may fail to service the debt.

Following interviews conducted, key participants from both operational as well as closed banks agreed that despite the type of model under use, for it to be considered effective, it should be able to facilitate 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.

The unstable macro-economic environment is characterised by largely unstable local currency, interest rates and high Inflation. Collectively, all these factors affect the purchasing power, deplete value of business income negatively, and drive the default rate. Consequently, poor loan performance results, as some clients may fail to adjust to new, elevated instalments. The Social Environment, which was exhibited by social unrests and poverty, resulted in an increase on default when borrowers lost their primary income source. The Political Environment is mainly motivated by politically-driven policies that often haunt banks; a good example cited by most interviewees was that of currency change, which has never been stable, from inception.

Key informants also raised concerns on the Internal Environment, as they alluded that management non-compliance was problematic, for example, failing to respect loan model outcome, but rather reverting to impulse-driven decisions in lieu of data-driven decisions. Often, the loan models provide useful predictive and prescriptive insights to ensure quality loans, however, divergent priorities by management overrule the action required from the loan model results or monitoring reports. The Technological Environment is mostly affected by data integrity, as well as limited technology investment by the bank. The success of loan portfolio is largely affected by the accuracy of data, as well as the availability of the skill and technology that can assist with computations. According to key informants from closed banks, they observed that more robust business intelligence systems tend to be very expensive, in terms of both the hardware and software licenses and as a result, a bank might choose to use an alternative, weak system with limited capacity to timeously detect arrears.

With reference to the Legal Environment, key concerns raised by participants related mainly to Government proclivity to change laws, with 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, which some economists disapprove of as violating the fundamentals of macroeconomics, as they have potential long-term repercussions.

Several other attributes that can show model effectiveness have also been identified in this study. These are that: a model can identify good clients, a finding that was

made by Lee and Chen (2005); Sustersic *et al.* (2009); Altman (2018). Accuracy is also propounded by Samreen and Zaidi (2012), Samreen *et al.* (2013), Chopra and Bhilare (2018), and Ziemba, Zalas & Becker (2020). To compare performing loans to the total loan book where a positive outcome is obtained was ranked the highest attribute of an effective model. This finding alludes to the position of Swamy (2015) and Thomas *et al.* (2017), who stated that effectiveness of a loan portfolio model can be validated by comparing performing loans to the total loan book, where the positive results displayed confirm the model's impact. Berg *et al.* (2020) and Philippon (2020) concurred that there is possibility of client discrimination if model techniques are not standard, consequently impacting efficiency.

Berger and Udell (2002), nonetheless, state that Asset-Based lending is primarily based on statistical financial ratios, security ratios and Credit Scores. Therefore, when there are incorrect computations, adequate security might be understated. Gerantonis (2009) found models, such as the Z-Score model's ability, is not constant; as a result, does not always identify good clients. Rama (2012) and Hurley and Adebayo (2017) argued that the Z-Score model is not accurate when Z-Scores are negative, which means it is not able to ensure security adequacy. The model does not always identify good clients; however, security adequacy is a result of loan model outcome, a finding in line with Japhet and Memba (2015).

On 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 Waweru and Kalani (2009), who observed that small market share of a business results in NPLs. Poor cashflows being generated by borrower can further result in poor loan performance, a finding made by Bessis (2010), who argues that inadequate cashflows cause NPLs, as borrower might have limited capacity to repay the loan. Bichanga and Aseya (2013) are of the view 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 decision-making by managers that is slow can cause poor loan performance.

Another factor identified is that an outdated loan model causes NPLs, with Mwengei (2013) and Roy (2014) having determined that using outdated lending models was

another factor that caused a rise in NPLs. Skarica (2014) posited that economic performance is an added factor that impacts loan performance. Insufficient technical competence in lending processes; inadequate MIS leading to untimely borrower creditworthiness information; introducing new financial products without thorough risk assessment and subjective decision-making due to lack of adequate client information, are further reasons highlighted by the RBZ (2014). Om'mbongo (2020), Kjosevski and Petkovski (2020) and Bredl (2018) brought it to light that NPLs were a result of high interest rates.

The key finding in this objective is that a loan model will not always identify good clients whose financial strengths may not be upset throughout the loan cycle. Theoretically, the findings align with financial intermediation theory and, remarkably, qualitative asset transformation, which aims to manage credit risk. The study argues that Commercial Banks mitigate credit risk through use of effective tools applied during credit assessment, which are loan models. Additionally, other theories used, namely; credit rationing, wherein the bank only extends clients a limit in line with its capacity to pay; portfolio theory, wherein the bank only invests in quality assets; and lender theory, wherein the bank ensures a fall back position in security, confirm correlation relationship with the study outcome. However, findings further reveal that even though a model may be effective to select bankable projects at the onset, other unforeseen circumstances such as poor planning, outdated models, declined market share and not respecting model outcome, may cause NPLs. These events or circumstances are not considered by the theories, making them weak in Zimbabwe.

In line with this finding, the study reveals that observing a loan model outcome, results in quality assets. Therefore, banks must adopt an appropriate loan model in line with types of loans, bank risk appetite, bank mandate and targeted clients. This work will equip commercial banks and academics with a practical approach, such as taking due diligence on applicability of the model on certain products. The study pointed out that outdated loan models influence an uninformed decision impacting loan performance. Therefore, additional knowledge is that any new inputs to the model must be robust, which will improve efficiency and effectiveness. While the type of loan model used partly contributes NPLs, the major factor that could be affecting efficacy of loan model is the harsh macro-economic and political situation

that fuels NPLs. Therefore, the study contribution is that key economic policies by government should be incorporated into loan models, while significant moderation, which influences models, is imperative for an economically and politically unstable economy such as Zimbabwe.

6.3.4 Objective 4: Influence of LPM Models on loan performance in Zimbabwean Commercial Banks

The fourth objective of this work was to assess the influence of LPMMs on loan performance in Zimbabwean Commercial Banks. It was hypothesised as follows:

Four hypotheses were used to address the objective:

H₁: The type of loan model used impacts loan performance.

H₂: Loan model parameter attributes used impact loan performance.

H₃: Loan model effectiveness impacts loan performance.

H₄: Loan model efficiency measures impact loan performance.

These hypotheses included H₁-H₃, with the reason for utilising these in objective 4 to validate the strength of the relationships of key loan model factors, namely; type of model (LPMM); parameter attributes (LPMA); model efficiency (EM); and model effectiveness. The results show that for the relationship between the LPMM and LP, $\beta = 0.616$ ($p = 0.038 < 0.05$). For the relationship between the LPMA and LP, $\beta = 0.357$ ($p = 0.046 < 0.05$). Third, for the relationship between LME and LP, $\beta = 0.736$ ($p = 0.000 < 0.05$). Last, for the relationship between LPMM EM and LP, $\beta = 0.420$ ($p = 0.003 < 0.05$). All measures had a statistically significant relationship with loan performance.

H₁: The type of Loan Portfolio Management Model used has an impact on loan performance

The relationship between the type of LPMM and loan performance was statistically significant. The Internal Credit Score Model has the strongest link in Zimbabwe Commercial banks.

Niresh and Pratheepa (2015) successfully established distressed companies using the Z-Score model, which is contrary to the study findings. However, this result

supports that of Abdou *et al.* (2016), who also hail the Internal Credit Score model as having a highly influential role on asset quality prediction or loan performance. The bank needs to take cognisance of the model results, especially when it indicates potential bad debt. In the USA aviation industry, the Z-Score model was deemed very accurate in predicting the financial status of companies (Hsu 2017). Therefore, comparing findings of the study with literature, it is not possible for one model to be practically applicable in all countries, especially developed and developing countries.

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

The relationship between LPMA and loan performance was statistically significant. This is a key finding for the Zimbabwean context, as no study has been done in this country on this aspect.

These findings allude to studies in other African countries, such as Kenya (Munene & Guyo 2013). In Ethiopia though, Pasha and Negese (2014) found that in the Agri-ecological regions, the high probability of loan performance is attributed to sufficient rainfall and not the model used. Muthoni (2016) found it more the characteristics of a borrower that influence loan performance, rather than parameter attributes. This means, notwithstanding sound parameters, the character of the borrower is also key in loan performance.

H₃: Loan model effectiveness has an impact on loan performance

This hypothesis tested positively, with a strong and significant relationship between model effectiveness and loan performance emerging. Effectiveness of a model, according to Yan *et al.* (2013) and Queirós, Faria and Almeida (2017), is strengthened by incorporating all data. Akram and Rahman (2018) advises that to improve model effectiveness, there is a need to ensure that its ratios can accurately measure liquidity and asset quality. It can, therefore, be concluded that when a model possesses the required inputs, respecting its outputs determines performing assets.

H₄: The loan model efficiency measures impact loan performance

The test revealed a strong relationship between model efficiency measures and loan performance. This was also a finding made by Berger, Barrera and Klein (2007), who

observed a positive correlation between credit scoring efficiency measures and loan performance. These authors further stated that using these efficiency measures is also beneficial in delinquency reduction, bringing greater clarity to the decision process and strengthening efficiency in advancing credit.

This objective was thus two-fold. First, the influence of LPMM on loan performance and second, bank failure.

The objective also sought to determine key reasons for the bank failure. From the evaluation of the interview results, various reasons emerged that could lead to bank failures in a developing nation such as Zimbabwe, as follows; corporate governance issues of not being an owner-managed institution that influences complacency by management; a weak board of directors made up of friends or relatives who try to protect their colleagues' interests; lack of disaster recovery mechanisms; and the use of outdated models; as well as poor markets; and poor planning. Generally, these factors corroborate the PESTLE factors examined in the preceding section, however, it places more blame on the internal environment.

Closed banks' former employees, especially from banks such as Time Bank, Barbican Bank and Royal Bank, expressed concerns on corporate governance issues and pointed to these as among the main reasons behind the fall of most Zimbabwean banks. They also cited weak management and the use of outdated models, hence, failure to detect small issues and the unsound financial position of borrowers before they face liquidation. Some key participants additionally cited the diversion of banks from their core business as they developed survival techniques, among which is letting them be engaged in speculative transactions, such as buying bricks for sale, investing in property (both immovable and moveable), which they did not have skills for. Consequently, funds ended up being locked in stock, hence, liquidity challenges and failure to generate new quality assets.

The findings of the study are in conformity with the financial intermediation theory, which among others, defines the role of a Commercial bank as that of brokerage, precisely issuance, banks in Zimbabwe are still initiating loans to clients. Also, Commercial banks performs qualitative asset transformation role, in particular credit

risk management achieved through the use of loan models and demonstrated by its positive impact on loan portfolio management. Hypothetically, all the other theories applied in this work, namely: credit rationing, portfolio theory and lender theory, which strengthens models, were in favour of some findings. Nonetheless, these theories did not address the issues to do with a consistent review of models, corporate governance, PESTLE factors, and diversion of bank business and outdated models, with all that impact loan model effectiveness.

In line with this finding, this study reinforces that loan models have significant influence from the onset towards loan performance prediction, however, important to note is that efficacy can decline due to unforeseen circumstances, which may result in poor loan performance. This study contributes to knowledge by reiterating that loan models ought not to be a one size fits all, but rather, they need to be customised to suit operating environments. In the context of Zimbabwe or a developing nation, it is imperative to develop custom solutions to ensure loan models remain highly accurate. Therefore, macroeconomics takes precedence. Additionally, banks should practice banking and leave other non-core business to either subsidiaries or special purpose vehicles; this will allow them ample time to monitor their loan portfolios, as well as timeously reviewing their loan models.

The study contribution is also a perspective from Southern Africa, focusing on Zimbabwe, with other countries that will also benefit from knowing what impacts loan performance when applying a loan model. This includes model type, parameter attributes, efficiency and effectiveness of the loan model, therefore, any deficiency will impact loan model performance. The study also established that an effective internal environment will reduce bank failures, as banks start to respect model results as well as corporate governance issues, with the authority to approve loans not done by one individual.

6.3.5 Objective 5: Circumstances that motivate Commercial Banks to enhance LM

The fifth objective of the study was to identify circumstances that motivate Commercial Banks to enhance a loan model or develop an internal model. It was hypothesised that;

H₀: Loan Portfolio Management Models (enhanced) do not have an impact on the loan performance of Zimbabwean Commercial banks.

H₅: Loan Portfolio Management Models (enhanced) have an impact on the loan performance of Zimbabwean Commercial banks.

The results 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 loan performance.

Furthermore, to establish this objective, model areas of improvement were evaluated. The data obtained from the respondents were subjected to the quantitative tools used in all the objectives. Most items used were highly ranked, with the topmost being the need to align the internal or local model with internationally developed models. Only one item was poorly rated, and this related to the non-use of the model results. The extraction showed the key model improvements should be model accuracy, model efficiency and model parameters.

Model accuracy was established from three items, which relate to the effect of the model on issues such as cost and credit culture. The items were model non-usage; the current model affecting the credit culture; the bank's model not being cost effective and the internal or local model that needs to be aligned to internationally developed models. Model parameters were established from two items, namely, the bank's model fully accommodates all qualitative details and the bank needs to have more variables in the model. These two items identified the deficiencies in the models being used. The results show the enhancement of a loan model would be as a result of scrutiny of weaknesses by the bank, especially when NPLs persist.

Seven key themes were extracted and these benefits were: the LPMM detects and distinguishes performing sectors from non-performing sectors; enables monitoring of borrowers; improves customer relationships; and increases profitability, while it also mitigates risk; shows the quality of the loan book; as well as being useful when diversifying portfolios. Generally, there was a consensus among participants that the

LPMM was very important as a risk-mitigation strategy, as well as for improving the profitability of the banks.

Qualitative results also revealed some of the challenges that banks faced in operationalising loan models, these include among them; unpredictable macro-economic environment, characterised by high interest rates and high inflation; perceived country risk requires review of variables often, which might be costly to the bank; and poor management culture, as some executives cannot distinguish between quality objectives, as well as growth objectivity, hence, overriding model results showing future company distress. The use of outdated data was also cited as one of the challenges. Again, this finding corroborates earlier findings where the high volatility of key macro-economic indicators tends to affect the modelling, given the data used for the modelling keeps changing, which entails the need to use more reliable and more current data.

Due to limitations in data warehousing and data architecture systems some banks, however, resort to the use of outdated data, which will negatively affect the model accuracy. The use of outdated data ultimately results in the creation of incompatible models and relates to the adoption of other models by some banks; however, these are not optimised for the Zimbabwean hyperinflationary environment. Consequently, this presents accuracy concerns, as the models created will not be compatible with the status quo.

The key informants nevertheless reiterated that loan performance has remained steadfast, because banks also strengthened their loan models by taking the following measures: ensuring the models are guided by central bank regulations; cost-effectiveness of the model; the loan model is aligned to credit policy; and adjusting variables in line with the macro-economic environment; as well as assessing the model history; reviewing parameters of loan models based on previous loan model performance; and gathering data that have made other market loan models successful.

The study findings support those of Ke *et al.* (2014) and Shen *et al.* (2019), who agreed that optimal utilisation of parameters result in enhanced accuracy and

efficiency of loan model prediction. Therefore, any weakness noted by the bank should be addressed through review of the model to strengthen or replace it entirely. The bank is motivated to improve its loan model when credit culture is weak. The results are also consistent with findings by Giannopoulos (2018), who states the local credit culture must be considered when evaluating a model. The findings reveal that for a bank model to be effective it is not one variable that strengthens the prediction and or accuracy. There is a need to consider a holistic approach, thus, examining unfolding events.

The second aspect of the objective was to develop a loan model which can be used by commercial banks. The success of the new loan model was underpinned by various processes which facilitated determination of model fit. Some notable processes are as follows:

Diagnostic tests: It was carried out to verify suitability of loan data hence determination of significance of the variables.

Testing for existence of outliers: was undertaken to eliminate data points which were far from other data points or all unusual values were eliminated from the dataset.

Testing for Multicollinearity: The main purpose was to identify correlation between independent variables and the strength of that correlation and was achieved through use of a statistical software which calculated the VIF (variance inflation factor) for each independent variable.

Solving Multicollinearity: A straightforward method used by the study to correct multicollinearity was by removing one or more variables which were showing a high correlation.

Fitting the Logistic Regression: It was fit to a set of data in order to estimate the parameters β_0 and β_1 . Accordingly, the straight-line fitting of the data was obtained by minimizing the distance between each dot of a plot and the regression line.

Final model: The results confirmed that the model was successfully developed exhibiting an efficacy rate of 87.80 percent. The use of many variables sometimes does not necessary yield an effective model but optimisation of variables with great significance or which influence prediction of default is very essential to apply in any loan model as demonstrated by the results. From the results it can also be substantiated that a model built using logistic regression reveal appropriateness of best variables to use, is easy to implement, interpret and shows probabilistic views of potential defaults which can assist the bank in making an informed decision. The technique may therefore, guarantee quality of the model and quickly distinct potential bad accounts from good accounts.

The success rate of the new credit score model is in line with observations made by other scholars who expressed satisfaction on the use of the logistic regression technique in building a loan model evidenced by better results compared to other loan models built by neural networks and genetic algorithms (Gouvêa & Gonçalves 2007). Furthermore, the logistic regression-built loan model is a regarded tool were much reliance maybe placed on when making loan predictions and has notable classification rate and outstanding AUC (Mestiri & Hamdi 2012). Whilst Costa e Silva *et al.* (2020) are buoyant with the logistic regression credit score following a 90 percent success rate in predicting default. The results however vary from Durand (1941), Samreen *et al.* (2013) and Guo *et al.* (2016), who have also developed credit score models using various techniques most notably discriminant analysis. It is also imperative to note that these scholars also recorded some successful results but not better than those from logistic regression model following their use of various variables including some which did not have any influence on loan default prediction.

The Financial intermediation theory that is underscored in this study, is apt in some of the findings, particularly, qualitative asset transformation, which aims to mitigate defaults through credit risk, hence loan performance. The study argued that through use of the enhanced loan model developed, the probability of reducing defaults is high. Furthermore, the credit rationing theory, portfolio theory and lender theory partially satisfied the findings, in the sense that they demonstrated the set loan models are able to provide potential loan. Nevertheless, these theories were shown to face practical difficulties in application, since it is impossible to consider every

potential risk and the market indices. The examination of results shows some challenges in implementing loan models guided by these theories, such as: macroeconomic environment; country risk, poor management culture and outdated tools. Furthermore, the findings show the theories do not fully guide banks on how to strengthen their models.

In line with the findings, this work contributes to the existing body of knowledge in the loan models domain, by providing some empirically tested insights in an African context, in a banking sector experiencing NPLs, and an uncertain economic and political environment. There is a need to refine the loan model by aligning it to the local business environment, thus for example ensuring economic factors are incorporated in the model, as well as with internationally developed models that have been tested and in existence for decades, arguably due to their soundness.

6.4 Concluding summary

The study findings were holistically discussed by linking them to the research objectives, hypotheses and research questions. Findings from the quantitative and qualitative findings were integrated and discussed by interpreting and relating the results to other findings found in the literature reviewed. Study findings found support for all the hypotheses developed for this study, with research questions adequately answered. The qualitative analysis played a very important role in this study, as it clarified and gave detailed explanations on some issues revealed in the quantitative results that would otherwise, still be puzzling; for example, the reasons behind the negative correlations between use of loan model and NPLs or bank failure. The following chapter presents the conclusions, study implications, study limitations and recommendations to various stakeholders in the banking sector.

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

This thesis is positioned to make a very significant contribution to the Financial Services industry, particularly in the African context. The investigation into loan model effectiveness in Zimbabwe Commercial banks, and the resultant findings in the country's banking sector, provided a novel analysis into loan performance in a developing country characterised by high NPLs, as well as the unstable macro-economic, social, legal, and political environment.

Literature reviewed shows loan models are sensitive to countries' economic climates; there are no one-size-fits-all situations. This is against the backdrop that access to finance is, in itself, an important economic driver. It was thus important to establish how effective the LPMs within Zimbabwe are, as they are crucial in loan decision-making. In prior chapters, reasons were provided for choosing to test three models; the Z-score, the Credit Score and the Asset-Based Models. One of the aspects this study established was, in Zimbabwe, the Z-score model is not favoured or in use by all the commercial banks. This suggests the model has limited capacity to select bankable corporates with an acceptable risk profile as required by the banks. The Internal Credit Score is the model utilised by the majority of commercial banks, exhibiting its compatibility and capacity to facilitate identification of bankable projects. Furthermore, the Asset-Based Model is being moderately utilised, it is not the best model while, at the same time, not the worst tool for selecting bankable projects. The study chapters are summarised below to reach the relevant conclusions and recommendations:

Chapter one navigated the identified problem to be solved in this study. Thereafter, the aim, research questions, study hypotheses, and objectives, as well as the methodology, were deliberated. This chapter also provided an overview of the banking sector in Zimbabwe, revealing the apparent banking crisis in Zimbabwe is actually a global phenomenon, which in the main, is caused by NPLs.

Chapter two discussed the broad financial architecture of Zimbabwe. To demonstrate LPM challenges, the study revealed all failed banks and the mitigation strategies put in place during the period under review. The chapter also offered an overview of financial sector evolution, exhibiting growth from pre- to post-independence. Financial systems in Africa were, likewise, reviewed and how they impact loan performance, particularly in Zimbabwe. Additionally, Zimbabwe government policies on economy were discussed, with the review of literature establishing how these policies impacted bank performance, specifically loan portfolios. The identified gaps in literature were as follows; loan models have no capacity to assess all clients in different sectors, eventualities may upset loan model results, and loan models can be outdated.

Chapter three mainly discussed theories that underpinned the study, namely financial intermediation, credit rationing, portfolio theory and lender theory. Furthermore, the chapter conceptualised each of the models under study by tracing their origins and showing how these were measured and tested in various countries. The strengths and weaknesses of the theories and models were also highlighted, along with how they may upset loan performance.

Chapter four outlined the research methodology used to collect data for this study. The theoretical framework to frame the research was discussed, along with relevant literature from theories. Sequential Explanatory design was used, because it involves both quantitative and qualitative data collection methods, with augmentation of the two methodologies allowing establishment of the objectives, due to explanations of the quantitative findings. The chapter detailed how the sample for the survey was selected and key informants purposively chosen, how they were approached and challenges faced, as well as how they were addressed. The chapter, furthermore, focused on how data were collected and analysed.

Chapter five presented, analysed and interpreted the findings of the study. Demographic information, respondent profiles, their experience, and designations were brought to the fore prior to the discussion of the survey results (quantitative). The study went on to test for reliability, validity and discriminant validity, which were measures of constructs. Thereafter, testing of objectives were undertaken and

achieved through KMO and Bartlett's test, Descriptive statistics, Factor analysis, as well as SEM, which tested study hypotheses. Qualitative data analysis was undertaken in this chapter, following the conducted interviews. This was achieved through the use of NVivo v1.3 data analysis software. Conventional content analysis and direct content analysis approaches were applied. Furthermore, axial coding was then carried out; hence, classification of tree codes. In addition, profiles of key informants were highlighted, with results showing all were experienced in banking, having worked in the sector for not less than 15years.

Chapter six reviewed what was set to be studied and the outcome thereof, discussing study results or empirical findings and the extent to which the objectives were established. The study findings were holistically discussed by linking them to the research objectives and hypotheses. Findings from the quantitative and qualitative results were integrated and discussed, in relation to the findings from the literature reviewed. The study further found support for all the hypotheses developed for this study. The qualitative analysis played a very important role, as it exposed many issues revealed in the quantitative results that would otherwise still be perplexing, while new details also emerged that assisted in shaping the study.

This chapter 7 now concludes the study by summarising the key study findings, discussing the study implications on theory and practice, as well as providing recommendations to key stakeholders. The study limitations are highlighted and recommendations given to guide future research.

7.2 Summary of results

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.

7.2.1 Research objective one

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

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 is shown to be more dominant, in contrast with internationally developed models such as the Z-Score model, suggesting 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 strength of the loan model's prediction.

Qualitative results: Key informants concurred 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 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). It can be further argued that either the novel approach in this study is needed or emphasis for a best loan model with variables skewed towards country risk, macro-economic fundamentals and climate change that impact businesses daily. The study also argued the Internal Credit score is the most suitable model in a perpetually volatile and unstable 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.

7.2.2 Research objective two

The second research objective sought to "examine the LPM Model parameter attributes currently used by Commercial Banks in Zimbabwe".

Quantitative results: The key findings from the study are that banks do not arbitrarily create loan model parameters, but are backed by several attributes, with among them being industry-based and past loan performance experienced. 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, accuracy of loan model is regarded as key.

For the loan model, the findings imply or mean 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.

7.2.3 Research objective three

The third research objective sought to “analyse the effectiveness of LPM Models and loan performance in Zimbabwean Commercial Banks.”

Quantitative results: With regard to loan model effectiveness, it was established that for a loan model to be considered as 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, 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 the technological environment were also indicated and are in line with postulations from Reece (2012). 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, resultantly 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. The study 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 evaluation stage. This work has, therefore, narrowed down the knowledge gap on the practicality of loan models, or effectiveness of loan models found many years ago in a stable environment, contrary to the current unstable environment in a developing nation such as Zimbabwe.

7.2.4 Research objective four

The fourth research objective sought to “establish the factors which influence LPM Models and causes of Commercial Banks failures”.

Quantitative results: The findings support all the established hypotheses, demonstrating a positive relationship on 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 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 uninformed decisions, resulting in default risk to the banks, impacting loan portfolio. The study findings enhance 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.

7.2.5 Research objective five

The fifth research objective sought to “Identify circumstances that motivate Commercial Banks to enhance a loan model and its impact on loan performance”.

Quantitative results: The findings substantiate that strengthening of a loan model is motivated by an observed weak loan portfolio, demonstrated by high NPLs and bank failures. Meanwhile, 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 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 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 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, credit policy, and by reviewing successes of competitors' loan models. Thereafter, the banks should learn and adopt some useful variables missing from their own loan models.

The study, therefore, argued that when the loan model is not aligned to 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.

7.3 Study limitations

These consist of events and unforeseen shortcomings possibly obstructing the study outside the researcher's control (Berg & Latin 2014; Thomas *et al.* 2011). Even though the research assistants did a sterling job in distributing and collecting questionnaires, the need remained for the researcher to travel the length and breadth of the target Provinces to support the assistants and open doors of certain Banks where difficulty was encountered. This posed a huge financial constraint for the researcher and some delay in consolidating the overall study findings.

7.4 Implication to stakeholders

The issues raised in this study and the findings may have some implications for the stakeholders such as the Banking Industry; the RBZ; the Government of Zimbabwe and all those seeking funding (borrowers).

7.4.1 Implications for Banking Industry

1. This study established that some NPLs were a result of outdated models, as well as use of outdated data. The study argues that any model which misses key variables and current data will be unable to identify all credit risks, with imminent default as a consequence. The banking Industry is, therefore, advised to tailor-make their loan models in line with external factors and timeously incorporate variables that address the risks posed by changes in political, social, economic, and technological, as well as environmental outlooks, climate change, and global epidemics. Fundamental to this, is the use of more variables which are relevant as much as possible, because each variable used mitigates a certain risk. Furthermore, banks should also try to explore other modern models, among them; support vector machine (SVM), artificial neural network (ANN), genetic algorithm (GA) and or machine learning (ML), which have proven to be effective in other developed nations (Berger 2004).

2. The study argues that NPLs are also attributed to banks not respecting the outcome displayed by the loan models at onset of the application, for example, granting a loan to clients who would have otherwise failed to meet the minimum

score, as opposed to declining the loan. The banking industry is, therefore, encouraged to respect their tried and tested models, whose set benchmarks are sufficient to indicate bankable and non-bankable projects. Additionally, banks should consistently review their loan models in line with the local and global business environment and, importantly, also review variable weights and scores.

3. Findings from this work also revealed not all loan models are compatible in meeting a bank's credit criteria, thus, selecting clients within its risk appetite. In addition, the study argued it is not always international loan models that can effectively identify best performing projects. The banking industry is, for these reasons, advised to undertake a thorough due diligence on any loan model before securing or utilising it. The recommendation is, notwithstanding the loan model being internationally recognised, the bank should ensure it is adjusted to meet the bank's risk appetite, the sector being targeted, and is aligned to bank credit policy and the macro-economic environment. It is very important for banks to select the most appropriate model with capacity to assess target clients' given product/s offered to the market and information availability. It should be on record that use of an inappropriate model on bank clients influences uninformed decisions.

4. It is also evident from the study that while loan models may be effective at onset of the loan, unforeseen market loss by the borrower upsets sales and causes NPLs (poor markets). The imperativeness of borrower market share is, therefore, emphasised to the banking industry, as it should be vigorously assessed by the bank. For example, before granting loans, there should be evidence of corporate orders, and or offtake agreements, and share or ratios of local and export markets. Banks should also assess any credit terms and evaluate their sustainability.

5. Social environment influences borrower behaviour, for example, borrowers assess sector performance and, when confidence falls, they deliberately stop servicing their loans, even should they have capacity. During the banking crisis, the rate of bank closure is high, which resulted in some borrowers who ceased to service their loans, thinking their bank could be closed, and got away without paying the debt back. Berry (1995) opines trust is a strong tool used to manage relationship; henceforth, banks should build enduring relationships with clients for mutual benefits, as well as

cementing trust, which will encourage clients to perform even when the sector is unstable.

6. The study also revealed that NPLs are a result of an unstable macro environment, characterised by high inflation and high interest rates passed on to the clients, and the loan instalment becomes costly. This implies the importance of Zimbabwean banks having to maintain a high degree of integrity and consistency in the delivery of their services, by showing respect and paying attention to all their customer needs. Notwithstanding interest rates being regulated by the Central Bank, it is recommended when the bank is lending its own funds from cheap deposits, it should levy low interest rates and not market rates. Furthermore, margins and service fees should be discounted significantly to produce lower instalments that will capacitate clients to service their loans, thus, mitigation of NPLs and prevention of bank closure. Services such as the provision of financial hardship advisory services and extended loan repayment options can assist customers to manage their debt, while also showing that banks are considering current customer needs. Exhibiting such a caring attitude is likely to mitigate existing low trust levels and will resonate well with most bank customers.

7. Bank closures have been a result of speculative business. To ameliorate the influence of business diversion, it is recommended banks should concentrate only on their core business where they have skills, and leave non-core business to subsidiaries or special purpose vehicles; these are companies formed only to execute such a transaction or other non-banking business activities. Nonetheless, banks may also consider partnering with NGOs or the government on some transactions, for instance, a joint venture with some NGOs facilitates use of cheap money, hence, on-lending it at a lower cost. This will mitigate NPLs and or bank closures. Additionally, partnering with government, for example to do low-cost housing units wherein government provides cheap land and the bank provides funding at a longer tenure, will reduce NPLs as low instalments will be paid.

8. The study developed a loan model that can be successfully used by commercial banks in Zimbabwe to evaluate bankable projects. It is, therefore, recommended banks utilise this model on new applications and only grant loans to applicants with

low default probabilities less than 0.5. This will reduce NPLs and improve loan quality, resulting in performing portfolios.

7.4.2 Implications to the Reserve Bank of Zimbabwe

1. This work has argued that outdated models cause NPLs. RBZ is the regulator of the Zimbabwean Banking sector, with the ability and power to access international regulators and financiers such as the World Bank and IMF and obtain credible information from these Institutions. The RBZ should thus provide the banking sector with all essential credit risk data or technical and financial structures obtained from international financiers, which may strengthen local loan models. Furthermore, failure of any bank impacts the country's entire financial system. The regulator should, therefore, consider affording technical assistance to banks with weak loan models that do not meet international standards and have high NPLs. The RBZ must strengthen and capacitate human skills of the industry, for example, by providing financial support to undertake studies on loan models as well as training on lending skills.

2. It is also evident from the study findings that loan model parameters are derived from industry and bank loan performance (own bank) and industry performance. The regulator should ensure its policies and guidelines are aligned to macro-economic fundamentals. This means implementation by RBZ should be transparent all the time to allow custodians such as commercial banks to not critique them but instead, implement and avoid poor alignment between banks and the central bank (RBZ). The bank custodians must desist from criticising these policies, as poor implementation across the industry impacts the industry as a whole. It is also recommended the RBZ and other key stakeholders share information on vital developments integral to the smooth functioning of the banking sector, especially on loan book. This information should then be disseminated to the banking industry in one unified voice. It is recommended a 'buddy system' be set up for failed parameters, allowing banks to share experiences and support each other. Banks can be provided with information and basic skills from RBZ to provide support and be therapeutic to each other.

3. The study also argued 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. Accordingly, it is recommended policy makers should ensure their policies are long-term and do not upset loan models in the short-term but should have a long lifespan. This will ensure NPL management starts from the top.

4. Social environment, which influences borrower behaviour, such as not servicing debts, is attributed to sector outlook and confidence level from the general populace. The RBZ must improve its public image, as well as that of commercial banks because, if left unattended, the current distrust in the banking industry (RBZ 2011) can further erode consumer confidence in the banking sector. Informal communication fuels speculative behaviours in the banking sector, for example, panic and anxiety when there are rumours of an imminent bank closure, which results in massive cash withdrawal demands that can cripple the banking system. As such, the RBZ has the responsibility to identify potentially volatile issues before they become unmanageable, and timeously communicate key developments occurring in the banking sector. It can, therefore, be argued identification of troubled banks and taking appropriate measures to secure bank customer deposits in these banks improves market confidence.

5. NPLs are also a result of corporate governance issues. Monetary authorities should set tight corporate governance tenets that can put an end to activities such as insider lending that end up defrauding depositors. Therefore, stiffer penalties should be introduced for banks found wanting or not respecting their own internal policies and loan model results.

6. Findings reveal outdated models and or outdated data as a cause of NPLs. It is recommended departments, such as Risk and Credit within the RBZ and in banks, are staffed by competent personnel likely to adhere to prudential standards of banking; hence, maintaining usefulness of the loan model in the industry. It is widely acknowledged that, in developing countries, the central bank cannot be completely independent from government activities, as it is expected to conform to the needs of the national economic strategies of the government, in order to boost economic development in a country (Bibow 2010). However, it is still recommended the RBZ has a degree of independence, leaving it free to plan and implement policies without

state interference, instead of being mostly driven by the political agenda. This is important in the current Zimbabwean banking scenario, in that the continuous association of the RBZ with government failures and politics can create a challenge for the central bank in portraying a trustworthy image, which is fundamental to restoring confidence in the sector.

7. Study findings show NPLs are a result of poor markets and cashflows. The RBZ should undertake thorough studies before pronouncing policies, especially on interest rates and exchange rates, which generally affect performance of various industries in the market. Therefore, the implemented policies should rein in and stabilise interest and exchange rates, as these influence funding cost. Better income to majority stakeholders expands available goods or services markets, improves high production volumes, and eradicates poverty, hence, low to no defaults by corporate borrowers.

8. Findings of the study depict the need for loan model enhancement, largely motivated by observed deficiencies in loan models, as demonstrated by NPLs. The regulator is, therefore, advised to continuously guide banks and encourage them to align their loan models with credit policy, market fundamentals and risk appetite. In framing banking sector policies, the central bank must balance the distinctive priorities of promoting financial sector development, innovation, and financial inclusion, limiting risks to financial sector stability; and providing adequate protection to banks, hence, macro policies should promote economic growth, resulting in production growth, which will facilitate corporate borrowers to increase sales and generate more income to service debt. This will ensure sustainability of loan models for longer periods and improve efficiency.

9. The credit scoring model developed by this work is a source of inspiration to the banking industry in general, as all banks may utilise it objectively. Using this model will result in all banks having their own robust loan models that will improve loan performance, thus helping RBZ to stabilise the sector. Effective loan models will reduce NPLs in the market, allowing RBZ to focus on other material issues, which can improve monetary policies. The reduction of NPLs through use of this effective

new model will result in more resources being available from RBZ for its duty as a lender of last resort, contrary to fund liquidity gaps caused by NPLs.

7.4.3 Implications for the Government

The study determined that among the major challenges of operationalising loan models and NPLs, was an unstable macro-economic environment. In the final analysis, the Government carries this responsibility. It is, therefore, recommended consistent policies that promote GDP growth in the country are implemented. It is also important for the government to monitor all macro-economic factors that grow the economy. Government might encourage Commercial Banks with quality loans by offering them tax breaks. According to Bülbül (2013), citizen confidence in financial institutions is critical for the long-term vitality of a nation's economy.

In developed countries, consumers have many options and have confidence in market mechanisms, with less reliance on government regulations (Asher 1998). This is contrary to the situation in developing countries, where consumers mostly rely on government intervention for protection (Al-Ghamdi, Sohail and Al-Khaldi 2007). Therefore, the government of Zimbabwe should protect its citizens by controlling and managing interest rates mutually through the central bank (RBZ), which is failing the banking public due to counterproductive policies and poor bank supervision. Also, from a development approach, the results suggests that the role of the state to create an enabling environment.

The new effective loan model will induce discipline in the market so that only creditworthy clients will access funding. The released liquidity from performing loans capacitates banks, hence, government will be able to access funding for its developmental projects, which will create employment and industry performance, resulting in a healthy GDP. Nonetheless, quality loans influenced by the new model improve sector confidence, thus, the government can use it to lure investors with a functional financial system. These investors will create employment, hence a better performing economy.

7.4.4 Implications for borrowers

1. The Internal Credit scoring model has been proven as 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. This makes it imperative for borrowers to know what exactly they are assessed on, which may equip clients with a comprehensive project proposal in place.

2. The study shows NPLs are a result of social environment, notably behaviour of clients who may deliberately ignore servicing monthly debts. Therefore, communication with existing and prospective clients is key to management of relations by the banks. Clients ought to be empowered by their bank, to enable them to plan properly, do a thorough market dissection, and develop an attitude change towards servicing loans. The banks should also be prepared to re-schedule loan repayments should clients have genuine reasons for non-payment. Clients need to know they have a role to play in keeping the bank liquid, as the bank's existence and provision of future loans are dependent on well-serviced existing loan. Clients must be willing to provide financial information whenever called for.

Findings reveal NPLs were also a result of an unstable macro-economic environment; one associated with high interest rates, exchanges rates and inflation, which make it difficult for clients to service their loans and or access new loans, because of high, unsustainable instalments. The recommendation is, therefore, for clients to reduce the amounts they borrow to sustainable levels and or negotiate for longer tenure, which should create capacity, and low defaults. In an effort to accommodate clients, the bank should be flexible on terms, in line with credit risk demonstrated by a client.

3. Bank failures are a result of weak corporate governance issues, with borrowers suffering most because they may lose their deposits. Clients who had not fully drawn on their facility will also lose the funding opportunity and their projects will be stalled. It is recommended clients peruse bank business conditions, publicly displayed in banking halls, and when the figures disappoint, it may be necessary to move to a sounder bank. Clients may also alert the regulator should they be aware of corporate governance shortcomings, in an effort to protect their interests.

4. The new credit score model will improve loan portfolio performance, which will enhance liquidity position of banks due to timeous payments of loan repayments. Therefore, better liquidity position of banks will facilitate new loans being granted to borrowers. Borrowers who do not respect their loan terms may fail to access funding in the near future, because this loan model considers prior borrower performance as one of the key variables that influence loan repayment prediction, thus instilling discipline.

7.4.5 Implications for Theory

The findings of the study revealed many causes of NPLs, with among these the unstable macro-economic conditions, political uncertainties, and outdated models. The credit risk theories that underpinned this study are; credit rationing, portfolio theory and lender theory. These theories aim to mitigate loan risk. Nevertheless, the drawback of the theories is they mainly focused solely on borrower characteristics, overlooking other extrinsic factors. Therefore, the performance of loan models cannot be dealt with in isolation, only considering borrower characteristics. It is recommended that a country overburdened by a highly volatile macro-economic milieu not rely on restrictive theories such as Credit rationing theory, as this assumes a stable environment, which is usually the case in developed economies. In this regard, there is a great need to redress this deficiency by adding new aspects to the theories. The study argues the need for a more holistic approach that considers both the individual attributes, as well as the context of the environmental factors. In this regard, any attempt to redress current problems resulting from poor loan model performance, should not solely consider borrower characteristics, but also other contextual factors. The inter-relatedness and inter-dependence of sub-systems, should these be considered, result in better loan models.

7.5 Avenues for Future Research

This study has only examined those tools used to assess the corporate loan application at 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 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 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 number of years in its existence has an influence on loan model performance based on loan book growth.
- iii **The security of the scoring system should also be studied.** Scoring is computer-based; this means, in the presence of cyber security challenges, including computer hijacking, it is important to ensure informed decisions are based on a secured system.

7.6 Conclusion

The study deals with the effectiveness of LPMM also referred to as loan models, arguing they are essential to ensure sustainable performance of Commercial Banks. Results proved that effective loan models yield quality assets, achieved through robust parameters, input and/or variables. It can be concluded the features of a loan model are what make it effective, consequently, facilitating selection of bankable projects by the banks. These findings confirm the results by Ugoani (2015).

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 policy and practice level impact 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 result 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 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 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 to

attract 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, 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 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 difficulty 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 will 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 has capacity to 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 (RBZ 2019). The proposed ranking is based on validation methods such as the correct classification rate (percentage), meaning accurate prediction by a model (Samreen & Zaidi 2012), as well as analysis of percentage of bad loans (Desai *et al.* 1995). 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.

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APPENDICES

APPENDIX 1



MANAGEMENT SCIENCES: FACULTY RESEARCH ETHICS COMMITTEE (FREC)

2 December 2020

Student No: 21647075

Dear Mr FT Matika

RECERTIFICATION - DPHIL: BUSINESS ADMINISTRATION

TITLE: Examining the effectiveness of loan portfolio management models on the performance of commercial banks in Zimbabwe.

Please be advised that the FREC Committee has reviewed your proposal and the following decision was made: **Ethical Level 2**

Date of FRC Approval: 27 November 2015

The Faculty Research Ethics Committee has granted your request for recertification for a period of **One year (From 2 December 2020)**, after which you are required to apply for safety monitoring and annual recertification. Please use the form located at the Faculty. This form must be submitted to the FREC at least 3 months before the ethics approval for the study expires.

Any adverse events [serious or minor] which occur in connection with this study and/or which may alter its ethical consideration must be reported to the FREC according to the FREC SOP's. Please note that ANY amendments in the approved proposal require the approval of the FREC as outlined in the FREC SOP's.

Yours Sincerely

Prof JP Govender
Chairperson: FREC

APPENDIX 2a

RESEARCH QUESTIONNAIRE

SECTION A: RESPONDENT'S PROFILE

1. Gender

Male	
Female	

2. Highest Educational Qualifications

High School	Attended College	First Degree	Postgraduate

3. Work Experience

0-5years	6-10years	11-15years	16years

4. Designation

Managing Director	Senior manager	Middle manager	Analyst/Officer

From Section B to Section E, kindly indicate by ticking on the appropriate box the answer of your choice.

SECTION B: LOAN PORTFOLIO MANAGEMENT MODELS EXISTENCE

5. The bank uses the Internal Credit Score Model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

6. The Bank uses the Z Score Model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

7. The bank uses Asset Based Model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

8. The bank uses various models on different loan products.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

9. A Loan Portfolio Management Model is a Score sheet used in analysing creditworthiness of a borrower.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

10. A Loan Portfolio Management Model is a ratio used in analysing creditworthiness of a borrower.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

11. A Loan Portfolio Management Model uses a multivariate method in analysing creditworthiness of an applicant.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

12. The bank measures model efficiency by comparing the number of defaults to performing assets.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

13. The Bank measures model efficiency by comparing type 1 error and type 11 errors.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

14. The bank measures efficiency by using non-performing ratio.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

15. Low facility management costs demonstrate efficiency of a model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

16. Turnaround time of a bank is viewed as a model's efficiency.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

SECTION C: MODEL PARAMETER ATTRIBUTES

17. The bank uses industry based parameters.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

18. Past loan performance experienced by a bank is considered when setting parameters.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

19. Parameters are initiated by bank or consultant.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

20. The model can incorporate sizeable factors such as financial and behavioural characteristics.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

21. Outcome probabilities of the model are pre-defined.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

22. A model's output can be ranked.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

23. The model's benchmark is well defined.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

24. The model is robust and is not reviewed or replaced often.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

SECTION D: THE EFFECTIVENESS OF LOAN PORTFOLIO MANAGEMENT MODELS AND LOAN PERFORMANCE.

25. A model is used to identify good clients.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

26. A Model ensures security adequacy.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

27. A model determines regular review of security.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

28. A model guides on measures to be taken when a loan is in doubt.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

29. A model guides the assessment of sister companies of a borrowing corporate client.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

30. A model is used to predict bankruptcy.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

31. A model determines non-performing loans.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

32. The level of performing assets is compared to the total asset book.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

33. Non-performing loans are caused by poor planning.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

34. Non-performing loans are a result of poor markets.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

35. Non-performing loans are a result of poor cash flows.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

36. Non-performing loans are caused by use of an outdated model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

37. Internally modified models result in quality loans.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

SECTION E: REASONS TO ENHANCE LOAN PORTFOLIO MANAGEMENT.

38. The bank no longer uses model results.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

39. The current model is affecting the credit culture.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

40. There are too many type 1 and type 11 errors from the current model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

41. The internal or local model needs to be aligned to internationally developed models.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

42. The bank has identified a need to have more variables on the model.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

43. The bank's model does not fully accommodate all the qualitative details.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

44. The bank's model is not cost effective.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

THANK YOU FOR YOUR TIME!!

APPENDIX 2b

INTERVIEW GUIDE FOR SENIOR RISK OFFICERS OF OPERATIONAL BANKS

SECTION A

Please note: The respondents must only write the number of their response except where they need to specify.

	Model used in the Bank	Economic Sector where model is used.	Success rate of the Model in predicting performance of Loan	Factors considered in developing a model.	Predictive power of each factor where 1 = low 5 = high
		1. Agriculture 2. Manufacturing. 3. Mining 4. Transport 5. Retail 6. Other – specify	1. 0-25% 2. 26-50% 3. 51-75% 4. 76- 100%	1. 2. 3. 4. 5. 6. 7.	
1	Internal Credit Score				
2	Asset Based Model				
3	Z Score Model				
4	5 Score Model				
5	Zmijewski Probit Score				
6	Ohlson O- Score				
7	Odom and Sharda 1990 Model				
8	Other - Specify				

Do you have anything more to add to the responses given above for example determination of model efficiency? -----

SECTION B

1. Which key parameters strengthens a Loan Portfolio Management model?.....
2. What are some of the characteristics of an effective loan model?-----

SECTION C

Would you say that the following environments have an impact on the effectiveness of Loan Portfolio Management Models on Loans? If so, how? Explain in detail.

1. Internal Environment (Bank)

2. The Political Environment

3. The Economic Environment

4. The Social Environment

5. The Technological Environment

6. The Legal Environment

7 Based on the bank crisis experienced in the past five years, how has your institution Loan Portfolio Management Model contributed towards managing the Loan Portfolio Management

.....

8. How do you determine effectiveness of bank Loan Portfolio Management Model?

.....

9. How do banks fail contrary to their claim that they use effective loan models?

.....

SECTION D

1. What other information do you think need to be known on the influence of Loan Portfolio Management models by banks?

.....

SECTION E

1. Why is it necessary to have Loan Portfolio Management in a banking crisis or in a normal environment?

.....

2. What are some of the constraints experienced, if any, in operationalizing Loan Portfolio Management models?

.....

3. How do banks strengthen their Loan Portfolio Management models?

.....

4. What are factors considered before your bank adopts a new Loan Portfolio Management model?

.....

5. How do you restore loan quality and minimise the impact of the bank crisis in future?

.....

6. Does technology enhance Loan Portfolio Management, briefly explain

APPENDIX 2c

INTERVIEW GUIDE FOR COLLAPSED BANKS EMPLOYEES (SENIOR RISK OFFICERS).

SECTION A

	Model that was used in the Bank	Economic Sector where model was used.	Success rate of the Model in predicting performance of Loan	Factors which were considered in developing a model.	Predictive power of each factor where 1 = low 5 = high
		1. Agriculture 2. Manufacturing. 3. Mining 4. Transport 5. Retail 6. Other – specify	1. 0-25% 2. 26-50% 3. 51-75% 4. 76- 100%	1. 2. 3. 4. 5. 6. 7.	
1	Internal Credit Score				
2	Asset Based Model				
3	Z Score Model				
4	5 Score Model				
5	Zmijewski Probit Score				
6	Ohlson O- Score				
7	Odom and Sharda 1990 Model				
8	Other - Specify				

7. Do you have anything more to add to the responses given above? -----

8 How did your bank determined loan model efficiency before its collapse? -----

SECTION B

1. Which parameters failed to influence Loan Portfolio Management model performance?.....

2. What were some of the characteristics of an effective loan model?-----

SECTION C

Would you say that the following environments had an impact on the effectiveness of Loan Portfolio Management Models on Loans? If so, how? Explain in detail.

1. Internal Environment (Bank)

2. The Political Environment

3. The Economic Environment

.....

4. The Social Environment

.....

.....

5. The Technological Environment

.....

6. The Legal Environment

7 Based on the bank crisis experienced in the past five years, how did your institution Loan Portfolio Management Model contributed towards managing the Loan Portfolio

Management.....
.....

8. What methods were used by your bank to determine effectiveness of bank Loan Portfolio Management model

.....

..

9. How did banks fail contrary to their claim that they were using effective loan models?

.....

SECTION D

1. What other information do you think need to be known on the influence of Loan Portfolio Management models by banks?

.....

SECTION E

1. Why was it necessary to have Loan Portfolio Management in a banking crisis or in a normal environment?

.....

2. What were some of the constraints experienced, if any, in operationalizing Loan Portfolio Management models?

.....

.....

3. How did your bank strengthen its Loan Portfolio Management model before its collapse?

.....

4. What factors were considered before your bank adopted a new Loan Portfolio Management model?

.....

5. How did your bank restore loan quality before it finally closed?

.....

.....

6. Did technology enhance your Loan Portfolio Management?

APPENDIX 2d



LETTER OF INFORMATION

Title of research study; **EXAMINING THE EFFECTIVENESS OF LOAN PORTFOLIO MANAGEMENT MODELS ON THE PERFORMANCE OF COMMERCIAL BANKS IN ZIMBABWE.**

Researcher: Fungai T Matika

Supervisor: Dr N. Potwana

Introduction and purpose of the study

The Commercial Banks in Zimbabwe generate income through interest earned on loans which largely determine the financial performance of the Banks. However, due to unforeseen circumstances some of these loans do not perform in line with the terms of the agreements resulting into defaults which will cost the Bank. The study seeks to examine the effectiveness of some predatory credit models being used by Commercial Banks in Zimbabwe thereafter making some recommendations which may mitigate high defaults being faced by Banks.

Procedure: Information will be collected through a questionnaire. This questionnaire will take at most 10 minutes to complete. The completed questionnaire shall be collected by the researcher upon completion or at an agreed date.

Risk or Discomfort: The probability of participants experiencing any physical, psychological, or social risks is non-existent.

Benefits: At this juncture it is important to note that there may be no immediate benefit to you through your participation in this study. It is however prudent to note that the results of the study will benefit the upcoming banking students, your institution, the Commercial Banks, the Central Bank, the Institute of Bankers and the Banker's association of Zimbabwe. The researcher has not been contracted by any commercial entity but for self-fulfilment and in line with college's prerequisite to complete a thesis before honoured with a Doctorate degree.

Alternatives: There are two choices either to participate in the study and or not to participate, however all the availed questionnaires should be returned on the due date.

Financial Information and Remuneration: There is no remuneration attached to participating in this study.

Confidentiality: All the information collected through the questionnaire will be treated in the strictest confidence and anonymity. Name and employers of the participants will not be required.

Contact Persons: Should you have any queries regarding this study and or related matters kindly contact the researcher or the supervisor whose contact details are given hereunder.

Student; Fungai T Matika **Mobile:** 0772471277 **Email:** ftmatika@yahoo.com

Supervisor; Dr N Potwana **Mobile:** 0027828607187 **Email:** nobubelep93@gmail.com



APPENDIX 2e

CONSENT

Statement of Agreement to Participate in the Research Study:

- I hereby confirm that I have been informed by the researcher, **Fungai Tichawona Matika** about the nature, conduct, benefits and risks of this study
- Research Ethics Clearance Number: _____,
- I have also received, read and understood the above written information regarding the study.
- In view of the requirements of research, I agree that the data collected during this study can be processed in a computerised system by the researcher.
- I may, at any stage, without prejudice, withdraw my consent and participation in the study.
- I have had sufficient opportunity to ask questions and (of my own free will) declare myself prepared to participate in the study.

Full Name of Participant Date Time Signature/Right thumbprint

I, **Fungai Tichawona Matika** herewith confirm that the above participant has been fully informed about the nature, conduct and risks of the above study.

Fungai Tichawona Matika

Full Name of Researcher

Date

Signature

Full Name of Witness (If applicable) Date

Signature

APPENDIX 3a

Turnitin Originality Report

- Processed on: 13-May-2022 22:15 SAST
- ID: 1460293760
- Word Count: 88719
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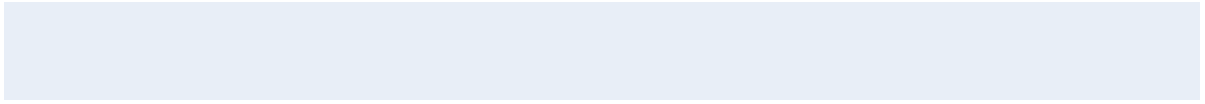
<https://www.mdpi.com/2071-1050/13/18/10398/html>

< 1% match (Internet from 29-Aug-2018)

Student Signature

Supervisor Signature: N. Potwana

Date: 25th May 2022



APPENDIX 3b

Helen Richter

Advanced Editing, Proofreading
& Copy writing

feetjieding@gmail.com
072 9538169

30 April 2022

To whom it may concern:

CERTIFICATE OF EDITING & AUTHENTICATION

I have proofread and language edited the following corrected PhD thesis titled:

**“EXAMINING THE EFFECTIVENESS OF LOAN PORTFOLIO
MANAGEMENT MODELS ON THE PERFORMANCE OF
COMMERCIAL BANKS IN ZIMBABWE”**

by

Fungai Tichawona Matika

The work is the author's own work, to the best of my knowledge, and remains free of spelling, grammar, and structural and stylistic errors.

With thanks.

H. S. Richter (Ms)

APPENDIX 4a

OFFICE OF THE MANAGING DIRECTOR

CABS



Northend Close,
Northridge Park,
Highlands
P.O. Box 2798,
Harare, Zimbabwe
Telephone: +263.4.883823,
Fax: +263.4.883804
E-mail: management@cabs.co.zw

18 July 2017

Durban University of Technology
Faculty of Management Sciences

P O Box 4000

Durban

South Africa

Dear Sir/Madam

Reference: Fungai T Matika

This letter serves to confirm that Fungai T Matika has been granted permission to do part of his academic research at CABS as requested.

Please be advised that we shall ultimately assist in the administration of the questionnaires.

Yours faithfully

Simon Hammond
Managing Director

APPENDIX 4b



TM/jm

July 10, 2015

Durban University of Technology
Faculty of Management Science
P O Box 4000
Durban
South Africa

Dear Sir/Madam

RE : PERMISSION TO UNDERTAKE STUDY

This letter serves to inform you that **Fungai T. Matika** has been granted permission to undertake study, interview employees and administer questionnaires as part of his studies for a Doctorial Degree with your University.

Please be assured that he will get maximum co-operation from us.

Yours faithfully

TSUNGAI MUNJERE
HUMAN RESOURCES MANAGER/EXECUTIVE DIRECTOR
GROUP HUMAN RRESOURCES & TRAINING

APPENDIX 4c



1st Floor, Unity Court, Kwame Nkrumah Avenue/First Street, Harare, Zimbabwe
Tel: (263-4) 7596511-9, 7596011-6 Fax: (263-4) 759648, Telex: 26392
Internet: <http://www.nmbz.co.zw> Email: enquiries@nmbz.co.zw

LC/ec/2906
29 June 2015

Durban University of Technology
Faculty of Management Science
P O Box 4000
Durban
South Africa

Dear Sir/Madam

FUNGAI T MATIKA

This letter serves to inform you that Fungai T Matika has been granted permission to undertake study, interview employees and administer questionnaire as part of his studies for a Doctorial Degree with your University .

Please be assured that he will get maximum co-operation from us.

Yours faithfully
For and On Behalf of NMB Bank Ltd


LIONEL CHINYAMUTANGIRA
EXECUTIVE DIRECTOR BANKING

APPENDIX 4d



Durban University of Technology
Faculty of Management Science
P O Box 4000
Durban
South Africa

Dear Sir/Madam

Ref: Fungai Matika

This letter serves to confirm that Fungai Matika has been granted permission to undertake study and administer questionnaire as part of his studies for Doctorial Degree with your University.

Please be guaranteed of utmost co-operation.

Yours faithfully

E. Chawoneka
Executive Director Banking

APPENDIX 4e



14th Floor, Old Mutual Centre
Cnr Third Street/Jason Moyo
P.O. Box 3200
Harare, Zimbabwe
Telephone: (263-4) 701636-52
Fax: (263-4) 708005
Website: www.mbca.co.zw
Swift Address: MBCAZWHX
E-mail: mbcabank@mbca.co.zw

Durban University of Technology
Faculty of Management Science
P O Box 4000
Durban
South Africa

2 July 2015

Dear Sirs

Fungai Matika- Doctoral Degree Programme

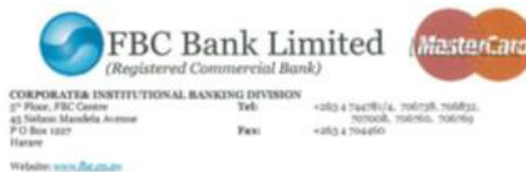
At the request of Fungayi Matika, a student of your University, who is undertaking a thesis research for the above degree programme, we wish to confirm that we undertake to assist with responses to the research questionnaires and interviews he may wish to conduct from MBCA Bank Limited.

Regards,

Herbert Chingono

Credit Manager

APPENDIX 4f



29 June, 2015

Durban University of Technology
Faculty of Management Science
P.O. Box 4000
Durban
South Africa

To whom it may concern,

RE: MR. FUNGAI T. MATIKA DOCTRAL STUDIES

We refer to the above and confirm that Mr. Matika has approached FBC Bank for assistance in carrying out his studies towards a doctoral degree with your University.

We confirm that FBC Bank will cooperate with Mr. Matika in his studies.

We hope you find this in order.

Yours Faithfully
For and on behalf of
FBC Bank Limited

.....
Martin Makonese
Executive Director, Corporate Banking

APPENDIX 4g

----- Forwarded Message -----

From: Dr. Lance Mambondiani <lance.mambondiani@stewardbank.co.zw>

To: ftmatika@yahoo.com <ftmatika@yahoo.com>

Cc: David Mapangela <david.mapangela@stewardbank.co.zw>; Ruka Nyoka
<ruka.nyoka@stewardbank.co.zw>

Sent: Monday, July 10, 2017, 03:46:40 PM GMT+2

Subject: FW: Request for permission to distribute questionnaire

Dear Fungai

Many thanks for your e-mail and please accept my apology for the delayed response. I am happy for you to do part of your research at Steward Bank as requested. I have therefore forwarded this email to David, our Head of Risk and Ruka (Head of HR), to assist you with your research.

Wishing you well with the completion of your studies.

Kind regards

APPENDIX 4h

From: tsitsi.r.mujuru@barclays.com <tsitsi.r.mujuru@barclays.com>
Sent: Thursday, 01 June 2017 10:22 AM
To: fmatika@idbz.co.zw
Subject: FW: Request to distribute questionnaires

For your file

Tsitsi R Mujuru | Dealer- Markets Sales | Treasury Front Office | Tel: +263 4 758280-9 Ext. 3221 | Mob: +263 776269000 | tsitsi.r.mujuru@barclays.com | Barclays Bank of Zimbabwe Limited | 6th Floor, Barclay House, First St/J Moyo Ave, Harare
www.barclays.com

Respect | Integrity | Service | Excellence | Stewardship
Helping people achieve their ambitions – in the right way.

From: Gatsi, Everson: BB Zimbabwe
Sent: 03 May 2017 12:39
To: Munyaradzi, Tsitsi: BB Zimbabwe
Cc: Mujuru, Tsitsi: BB Zimbabwe; Chaibva, Belinda: Barclays Non-Core
Subject: RE: Request to distribute questionnaires

Good day,

Please take this as Compliance approval.

Regards,

Everson

Appendix 5

APPENDIX 5



Date: 10 July 2017

Dear Sir/Madam

Request for a list of Lending Personnel

I refer to our meeting of 15 June 2017 where I requested that the Bank furnishes me with all the staff members who are involved in Bank Lending.

I would be very pleased if the list could be formatted as follows:

Name of Participant	Department	Province	Managerial	Operational	Sex

I thank you in anticipation



Fungai Matika

APPENDIX 6a

Z Score Computation for Failed banks

	Bank Name	Total sales	Retained Earnings Before Interest	Retained earnings	Working Capital	Equity Mkt Value	Total Assets	Book Debt
1	Genesis	394,669.40	-2,530,570.67	-2,530,570.67	521,017	-2,139,622	3,407,080	1,955,819
2	Renaissance	12,575,679.13	-17,804,577.35	17,804,577.35	-8,788,397	-18,624,588	101,064,797	44,786,577
3	Tetrad	2,721,419.69	915,455.43	915,455.43	-3,176,011	13,613,878	73,670,282	36,851,189
4	Royal	92,579.63	4,557,995.65	3,987,847.65	-3,495,280	4,274,228	12,673,507	1,266,459
5	Trust Bank	5,327,002.69	4,399,779.09	4,374,955.84	-36,392	12,980,693	39,424,860	22,734,197
6	ZABG	1,059,910.29	-5,365,065.60	-5,271,514.87	-2,346,431	8,424,957	17,416,882	5,909,604
7	Intermarket Bank	105,041.28	392,673.74	369,129.74	398,433	871,153	1,883,927	547,166
8	Interfin Bank	27,791,568.46	-3,549,543.62	-1,488,291.85	20,648,586	19,669,006	212,931,453	78,468,627
9	Kingdom	27,022,860.82	935,217.73	587,392.54	-1,442,113	13,285,713	150,521,537	97,790,659

		Genesis	Renaissance	Tetrad	Royal	Trust	ZABG	Intermarket Bank	Interfin Bank	Kingdom
1	Working Capital	521,017	- 8,788,397	- 3,176,011	- 3,495,280	- 36,392	- 2,346,431	398,433	20,648,586	- 1,442,113
	Total Assets	3,407,080	101,064,797	73,670,282	12,673,507	39,424,860	17,416,882	1,883,927	212,931,453	150,521,537
		0.15	0.09	0.04	0.28	0.00	0.13	0.21	0.10	0.01
2	Retained Earnings	- 2,530,571	- 17,804,577	- 915,455	- 3,987,848	- 4,374,956	- 5,271,515	369,130	- 3,549,544	- 935,218
	Total Assets	3,407,080	101,064,797	73,670,282	12,673,507	39,424,860	17,416,882	1,883,927	212,931,453	150,521,537
		0.74	0.18	0.01	0.31	0.11	0.30	0.20	0.02	0.01
3	EBIT	- 2,530,571	- 17,804,577	- 915,455	- 4,557,996	- 4,399,779	- 5,365,066	392,674	- 3,549,544	- 935,218
	Total Assets	3,407,080	101,064,797	73,670,282	12,673,507	39,424,860	17,416,882	1,883,927	212,931,453	150,521,537
		0.74	0.18	0.01	0.36	0.11	0.31	0.21	0.02	0.01
4	Market Value of Equity	- 2,139,622	- 18,624,588	- 13,613,878	- 4,274,228	- 12,980,693	- 8,424,957	871,153	19,669,006	13,285,713
	Book Value of Total Liab.	1,955,819	44,786,577	36,851,189	1,266,459	22,734,197	5,909,604	547,166	78,468,627	97,790,659
		1.09	0.42	0.37	3.37	0.57	1.43	1.59	0.25	0.14
5	Sales	394,669	12,575,679	2,721,420	92,580	5,327,003	1,059,910	105,041	27,791,568	27,022,861
	Total Assets	3,407,080	101,064,797	73,670,282	12,673,507	39,424,860	17,416,882	1,883,927	212,931,453	150,521,537
		0.12	0.12	0.04	0.01	0.14	0.06	0.06	0.13	0.18
		Genesis	Renaissance	Tetrad	Royal	Trust	ZABG	Intermarket Bank	Interfin Bank	Kingdom
	Z-score	- 2.31	- 0.38	- 0.39	- 3.78	- 0.93	- 0.74	- 2.26	- 0.44	- 0.32

APPENDIX 6b

2013 Commercial Banks Loan Portfolio Analysis

	Metbank	Ecobank	FBC	CABS	CBZ	NMB	STANCHART	ZB BANK	Banc ABC	Steward bank	Barclays
Total loans	102,347,406	92,924,000	265,760,858	322,310,630	898,988,379	181,316,271	180,684,221	146,207,271	325,054,000	119,321,627	115,432,369
Total assets	169,015,174	127,067,000	452,346,832	623,307,847	1,427,833,599	259,483,112	424,795,278	348,440,727	527,146,000	184,930,091	307,806,497
Total deposits	118,373,280	83,260,000	228,936,273	461,575,164	1,303,981,360	211,215,066	314,393,769	218,615,988	390,043,000	103,179,792	248,130,341
Non-performing loans	11,686,941	7,433,920	24,019,060	33,377,301	45,764,666	38,730,878	12,235,682	29,790,265	45,552,000	15,497,015	1,094,997
Ratios											
Total Loans/ Total Assets	61%	73%	59%	52%	63%	70%	43%	42%	62%	65%	38%
Non-Performing Loans/ Total Loans	11%	8%	9%	10%	5%	21%	7%	20%	14%	21%	1%
Total Loans/Total Deposit	86%	112%	116%	70%	69%	86%	57%	67%	83%	116%	47%

Source; Commercial Banks Annual reports

2013

Ratio Type	Average Ratios
Total Loans/ Total Assets	52
Non-Performing Loans/ Total Loans	10.58
Total Loans/Total Deposit	75.75

APPENDIX 6c

2014 Commercial Banks Loan Portfolio Analysis

	Metbank	Ecobank	FBC	CABS	CBZ	NMB	STANBIC	STANCHART	ZB	Banc ABC	Steward bank	Barclays
Total loans	64,668,718	127,901,000	314,421,853	443,529,711	960,874,733	203,363,052	234,423,000	200,007,472	151,593,793	358,963,000	67,612,307	121,748,395
Total assets	159,455,989	157,524,000	477,348,003	852,354,131	1,518,413,377	286,049,034	560,955,000	407,732,686	383,062,610	491,989,000	138,746,577	292,848,301
Total deposits	107,950,491	111,035,000	282,451,209	651,465,582	1,392,496,591	235,362,677	449,684,000	293,811,250	243,818,336	353,327,000	62,119,670	206,580,622
Non-performing loans	59,271,471	8,953,070	34,117,131	35,009,550	84,179,167	38,581,699	20,607,000	13,356,645	48,785,231	91,414,000	4,604,466	2,470,924
Ratios												
Total Loans/ Total Assets	33%	81%	66%	52%	63%	71%	42%	49%	40%	73%	49%	42%
Non-Performing Loans/ Total Loans	91%	7%	10%	8%	8%	18%	8%	7%	32%	25%	7%	2%
Total Loans/Total Deposit	49%	115%	111%	68%	69%	86%	52%	68%	62%	102%	109%	59%

Source; Banks Annual reports

2014

Ratio Type	Average Ratios
Total Loans/ Total Assets	55
Non-Performing Loans/ Total Loans	18.58
Total Loans/Total Deposit	79

APPENDIX 6d

2015 Commercial Banks Loan Portfolio Analysis

	Metbank	Ecobank	FBC	CABS	CBZ	NMB	STANBIC	STANCHART	ZB	Banc ABC	Steward bank	Barclays
Total loans	28,670,928	165,839,000	282,971,693	562,340,000	883,467,862	232,546,908	254,272,000	163,302,083	112,119,490	323,535,000	62,839,226	145,346,000
Total assets	157,899,853	233,952,000	490,565,322	1,042,940,000	1,814,126,770	333,831,107	594,940,000	383,316,400	417,625,071	490,206,000	164,635,763	299,311,000
Total deposits	38,834,098	165,571,000	287,416,228	829,080,000	1,652,596,210	277,216,769	484,050,000	291,611,573	269,697,449	336,932,000	87,685,312	234,211,000
Non-performing loans	21,991,908	13,267,120	2,899,037	43,760,000	76,622,466	8,582,636	20,938,000	9,988,021	23,948,042	95,982,000	21,993,729	2,542,000
Ratios												
Total Loans/ Total Assets	18%	71%	58%	54%	49%	70%	43%	43%	27%	66%	38%	49%
Non-Performing Loans/ Total Loans	77%	8%	1%	8%	9%	4%	8%	6%	21%	30%	35%	2%
Total Loans/Total Deposit	74%	100%	98%	68%	53%	84%	53%	56%	42%	96%	72%	62%

Source; Banks Annual reports

2015

Ratio Type	Average Ratios
Total Loans/ Total Assets	48.8
Non-Performing Loans/ Total Loans	17.41
Total Loans/Total Deposit	71.5

APPENDIX 6e

2016 Commercial Banks Loan Portfolio Analysis

	Metbank	Ecobank	FBC	CABS	CBZ	NMB	STANBIC	STANCHART	ZB	Banc ABC	Steward bank	Barclays
Total loans	21,477,748	132,804,000	276,534,813	583,250,000	873,999,508	195,492,260	273,486,000	125,140,962	109,578,654	235,571,000	57,947,574	173,522,000
Total assets	201,272,415	395,482,000	610,144,717	1,073,100,000	1,912,591,402	320,984,926	845,524,000	504,006,627	439,292,796	419,374,000	168,692,986	476,210,000
Total deposits	53,441,115	329,461,000	370,117,494	845,050,000	1,735,423,213	260,550,383	702,225,000	397,319,679	275,272,254	290,050,000	92,649,977	393,961,000
Non-performing loans	686,834	664,020	9,218,523	49,920,000	70,622,426	8,305,117	22,662,000	4,661,302	25,975,323	63,382,000	7,822,922	2,388,000
Ratios												
Total Loans/ Total Assets	11%	34%	45%	54%	46%	61%	32%	25%	25%	56%	34%	36%
Non-Performing Loans/ Total Loans	3%	1%	3%	9%	8%	4%	8%	4%	24%	27%	14%	1%
Total Loans/Total Deposit	40%	40%	75%	69%	50%	75%	39%	31%	40%	81%	63%	44%

Source; Commercial Banks Annual reports

2016

Ratio Type	Average Ratios
Total Loans/ Total Assets	38
Non-Performing Loans/ Total Loans	8.8
Total Loans/Total Deposit	53