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# ORGANIZATIONAL FACTORS INFLUENCING THE CREDIT RISK MANAGEMENT STRATEGIES BY DIGITAL CREDIT PROVIDERS IN KENYA

**HANAFI SHEIKH ABDI ALI**

**MDF/ 171681**

**A RESEARCH THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN DEVELOPMENT FINANCE**

**STRATHMORE UNIVERSITY BUSINESS SCHOOL**

**NAIROBI, KENYA**

**JUNE 2026**

## DECLARATION

I declare that this work has not previously been submitted or approved for the award of a degree at this or any other university. To the best of my knowledge and belief, this thesis contains no material that has been published or written by another person, except where proper acknowledgement and reference have been made within the thesis.

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**Hanafi S. A. Ali**
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Signature…… ….....Date.... 14th June 2026.....

**Approval**

The thesis of Hanafi Ali was reviewed and approved for examination by:

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**Strathmore University Business School**



Signature…….... ..... Date.....14th June 2026.....

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## ABSTRACT

Digital lending has transformed access to credit using digital technologies, leading to the rapid growth of Digital Credit Providers (DCPs) in Kenya. However, increased access to credit has also heightened concerns regarding credit risk, loan defaults, and consumer protection. In response, the Central Bank of Kenya introduced Digital Credit Provider regulations in 2022 to strengthen consumer protection and influence credit risk management practices within the sector. Guided by the Resource-Based View and Prospect Theories, this study examined the credit risk management strategies employed by DCPs, the organizational factors influencing their adoption, and management perceptions regarding their effectiveness. The study adopted positivist and post-positivist philosophies and utilized mixed-methods research design. Primary data were collected through online semi-structured questionnaires administered to licensed Digital Credit Providers in Kenya. The findings from 93 DCPs indicate that Digital Credit Providers employ various credit risk management strategies, including loan structuring and limits, automated collection and warning systems, dynamic credit scoring models, and partnerships or credit guarantees. Organizational characteristics such as years of operation, firm size, and credit management training were found to influence the adoption of selected credit risk management strategies. The study further established that DCPs are increasingly leveraging artificial intelligence, machine learning, alternative data, and adaptive credit scoring models to enhance credit risk management. However, the implementation of these technologies is constrained by technical challenges, limited availability of quality data, and regulatory requirements relating to data privacy and consumer protection. The study concludes that the future of digital credit risk management will depend on balancing technological innovation, regulatory compliance, and consumer protection. It recommends increased investment in advanced analytics and data infrastructure by DCPs, strengthening regulatory frameworks by policymakers, and support for capacity building and governance by investors and development partners. Further research should examine digital lending practices across different jurisdictions and institutions to enhance the sustainability and effectiveness of credit risk management strategies.


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## LIST OF ABBREVIATIONS

| | |
|---|---|
| AML | Anti Money Laundering |
| CBK | Central Bank of Kenya |
| CFT | Countering the Financing of Terrorism |
| CRB | Credit Reference Bureau |
| CRM | Credit Risk Management |
| DCP | Digital Credit Providers |
| DFS | Digital Financial Services |
| ERM | Enterprise Risk Management |
| FSD | Financial Sector Deepening |
| GMM | Generalized Method of Moments |
| KYC | Know Your Customer |
| NPL | Non-Performing Loans |
| PAR | Portfolio at Risk |
| PT | Prospect Theory |
| RBV | Resource-Based View |
| USSD | Unstructured Supplementary Service Data |
| VRIN | Valuable, Rare, Inimitable, Non-substitutable |

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# DEFINITION OF TERMS

| | |
|---|---|
| Digital Lending | Granting and managing loans using digital platforms, usually without the requirement for in-person communication or conventional paper-based procedures. (BIS, 2018; Fuster et al., 2019) |
| Credit Risk | The potential for a borrower or counterparty to default on their financial commitments, causing the lender to suffer financial loss. (Hull, 2018) |
| Credit Risk Management | The process of identifying, assessing, monitoring, and controlling the risk of financial loss arises when borrowers or counterparties fail to meet their contractual obligations. (Saunders & Allen, 2020) |
| Consumer Protection | Laws, rules, guidelines, and procedures created to protect consumers from unfair, dishonest, or harmful commercial practices. (World Bank, 2017) |
| Anti Money Laundering (AML) | The laws, rules, policies, and practices intended to stop criminals from passing off money gained unlawfully as legal income. (FATF, 2021) |
| Know Your Customer | Also called (KYC) Know Your Customer (KYC) in lending refers to the process of verifying the identity and background of a borrower before providing a loan, to ensure they are who they claim to be and to assess their credibility. (FATF, 2021) |

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# CHAPTER ONE: INTRODUCTION

## 1.1 Background of this study

Digital credit providers (DCPs) are financial institutions or fintech firms that provide short-term credit products through digital delivery channels, frequently without direct physical contact with clients (Meier & Sprenger, 2010). These are companies leveraging mobile technology along with data analytics and algorithms to underwrite loans, disburse them and collect them (Owens et al., 2018). The role that they play in promoting financial inclusion is particularly important, albeit under research in poorer and unbanked sections of society (Cook & McKay, 2015). They include mobile phone companies, who offer credit through mobile money platforms (such as Safaricom's Mpesa), Fintechs using proprietary technology (e.g., Tala, Branch, Zenka), Banks and Microfinance Institutions (MFIs) and Neobanks and Digital Banks that offer comprehensive digital financial services, including credit, via apps or web platforms (Kowalewski et al.,2022).

However, even with the rise of digital lending, many customers still preferred traditional avenues to accessing credit- the commercial & microfinance bank. But demand for and supply of digital credit products increased because of the COVID-19 downturn in late 2019 to early 2020 (Suri & Jack, 2016). Digital credit providers in Kenya flourished and the proliferation of licensed and unlicensed digital credit providers was reported (FSD Kenya, 7 2023). Furthermore, credit risk increased as borrowers experienced financial distress, which in many cases resulted in loan defaults. To recover overdue amounts, some digital credit providers employed a range of debt collection practices, including both lawful and unlawful measures. For instance, certain providers reported defaulters to credit reference bureaus (CRBs), made repeated or threatening phone calls, and contacted borrowers' acquaintances by sending messages that disclosed the outstanding balances. These practices were used as mechanisms for managing credit risk and pursuing recovery of defaulted loans.

In response to rising concerns among customers and other stakeholders regarding digital credit services, the Central Bank of Kenya (CBK) issued the Digital Credit Providers (DCP) Guidelines in 2022. These guidelines require all digital credit providers to obtain licensing from the CBK, thereby ensuring compliance with consumer protection standards and anti-money laundering (AML) requirements. A key focus of the regulations is consumer protection, particularly through

mandatory disclosure of credit terms and conditions clearly and transparently. This includes interest rates, fees, and any additional charges associated with credit products. In addition, DCPs are required to adopt fair and respectful debt collection practices that avoid harassment or undue pressure on borrowers (CBK, 2022).

These regulatory requirements have important implications for the credit risk management strategies available to DCPs. Considering the rapid expansion of digital credit services and their contribution to financial inclusion, a growing body of empirical research has examined digital financial services and credit. For example, prior studies have explored the origins and innovations in digital financial services (Francis et al., 2017), factors enabling their growth and adoption (Chen & Mazer, 2016), risk management practices within digital finance, and the role of regulation in shaping digital financial services (Pavlidis, 2021). However, given the persistent operational and regulatory challenges facing digital credit providers in Kenya, this study aimed to contribute to the existing empirical literature by examining the strategies that DCPs are prioritizing to mitigate and manage credit risk in the context of the CBK's 2022 regulatory framework.

The rest of the chapter provides background information on digital credit providers, credit risk management strategies by digital credit service providers, a highlight of the research gap, the problem statement, the research objectives and questions, the significance of the study, and scope, and concludes with a summary of the research.

### 1.1.1 Digital Credit Providers (DCPs)

The rapid advancement of digital technology has substantially reshaped the financial services sector, leading to the emergence and expansion of Digital Financial Services (DFS). DFS refers to financial products and services that are accessed and delivered through digital channels such as mobile phones, payment cards, the internet, and point-of-sale (POS) devices. The development of DFS can be traced to the early 2000s, particularly with the introduction of mobile money platforms in emerging markets. In Kenya, the launch of M-Pesa by Safaricom in 2007 represented a major turning point in this evolution. By enabling users to deposit, withdraw, and transfer funds using mobile phones without the need for a traditional bank account, M-Pesa significantly broadened access to formal financial services (Jack & Suri, 2011). This innovation provided a critical

foundation for subsequent developments in digital banking, mobile payments, and, ultimately, digital credit services.

The global financial inclusion agenda driven by institutions such as the World Bank and the GSMA has further accelerated the growth of digital financial services by supporting digital infrastructure development, promoting enabling regulatory frameworks, and encouraging public–private partnerships (World Bank, 2014). Within this broader ecosystem, digital credit providers (DCPs) have become increasingly important in advancing financial inclusion, particularly among underserved and unbanked populations.

First, DCPs expand access to credit by extending loans to individuals who lack formal credit histories, often relying on alternative data sources such as mobile phone usage patterns, transaction records, and social network information to assess creditworthiness (Chen & Mazer, 2016). Second, they contribute to economic empowerment by offering fast and typically short-term credit that can assist small businesses and households in addressing cash-flow constraints, responding to emergencies, and smoothing income fluctuations (CGAP, 2020). Third, DCPs have stimulated innovation in credit scoring by pioneering the use of machine learning techniques and big data analytics to evaluate credit risk, thereby enabling scalable and cost-efficient lending models (Frost et al., 2019).

Despite the significant benefits associated with digital credit, its rapid expansion particularly in weakly regulated environments has raised concerns related to over-indebtedness, consumer protection, and regulatory arbitrage. Digital credit providers (DCPs) typically assess creditworthiness using alternative data sources, including mobile phone records (such as call logs, SMS activity, and location data), social media information, and customers' transaction histories (Björkegren & Grissen, 2017). Credit decisions are often automated and made within seconds through algorithmic models, with approved loans disbursed almost immediately to borrowers' mobile wallets or bank accounts.

Most digital loans are offered as microloans with relatively short repayment periods typically ranging from seven to ninety days making them suitable for meeting day-to-day financial needs or addressing emergencies. Repayments are also made through digital channels (Cook & McKay, 2015). However, some DCPs have been reported to employ aggressive debt collection practices, which have intensified concerns regarding the protection of consumer rights. In terms of business

models, DCPs commonly generate revenue through interest charges, transaction fees, and default penalties. In some cases, providers also derive value by monetizing user data and establishing partnerships with credit bureaus.

Globally, over 1,000 digital lenders operate across various regions. The majority are concentrated in Asia, especially in countries like India, China, and Indonesia. According to the World Bank Global Findex Database (2021), digital loans are growing rapidly in low- and middle-income countries. In Africa, digital credit has expanded notably due to high mobile penetration. There are an estimated 400+ digital lenders across the continent, with key markets including Nigeria, Kenya, South Africa, Tanzania, and Uganda (GSMA, 2022). Kenya is one of the most vibrant digital credit markets in the world. As of 2023, the Central Bank of Kenya (CBK) had received over 450 applications for digital credit licenses, and 153 providers were licensed by September 2025 (CBK, 2025). Popular DCPs include Tala, Branch, Zenka, M-Shwari, KCB M-Pesa, and Okash.

### 1.1.2 Credit Risk Management Strategies for Digital Lending

Digital credit providers (DCPs) extend short-term, unsecured loans through digital platforms such as mobile applications and Unstructured Supplementary Service Data (USSD) channels. In many cases, their operations operate outside traditional banking infrastructure, instead leveraging automated, algorithm-driven decision-making and alternative data to assess borrower eligibility. Because DCPs frequently serve borrowers with limited credit histories and typically do not require collateral, effective credit risk management constitutes a central operational priority and a key strategic concern.

Digital credit providers developed at the convergence of mobile money innovation, financial inclusion initiatives, and broader fintech advances, particularly in low- and middle-income countries. An important foundation was the emergence of mobile money platforms, such as Safaricom's M-Pesa in Kenya, which was piloted in 2005 and scaled nationally from 2007. M-Pesa established a dependable digital payments infrastructure that operated largely outside the conventional banking network, enabling widespread access to electronic transactions.

Building on the reach of mobile money and the policy emphasis on expanding financial inclusion, formal digital credit products began to emerge. In Kenya, for example, M-Shwari, a digital savings-and-loan product accessed through M-Pesa, was launched in November 2012 through a

partnership between Safaricom and the Commercial Bank of Africa (CBA). The product enabled users to save small amounts and access short-term microloans, typically repayable within approximately 30 days, even in the absence of traditional collateral or extensive credit histories (Tetteh, 2023).

After these early pioneers, digital credit providers expanded rapidly. Non-bank fintechs entered the field, offering app-based instantaneous or near-instant loans, using alternative data for credit scoring (such as mobile usage, airtime top-ups, transaction behavior) rather than traditional collateral. (Tetteh, 2023).

Credit risk refers to the likelihood that a borrower will be unable or unwilling to meet their debt obligations as they fall due. For digital credit providers (DCPs), effective credit risk management is critical for financial sustainability, as it helps limit default rates while supporting consumer protection within high-volume, low-margin lending models (Frost et al., 2019).

Compared with traditional lenders, DCPs operate in an environment shaped by limited availability of conventional credit data, small loan amounts with short repayment periods, large volumes of transactions, minimal direct lender–borrower relationships, and the prevalence of multiple borrowing across different providers. These structural features create distinct risk exposures and necessitate innovative credit risk management approaches that extend beyond traditional credit appraisal methods (Chen & Mazer, 2016).

Digital credit providers (DCPs) assess creditworthiness using a wide range of non-traditional data sources, including mobile phone usage patterns (such as call activity, SMS frequency, and airtime purchases), transaction records from mobile money platforms, and, in some cases, social media activity, geolocation data, device metadata, and app usage behavior. Machine learning techniques are then applied to analyze these datasets and generate credit scores that estimate the probability of default (Björkegren & Grissen, 2018). This data-driven approach enables DCPs to extend credit to unbanked individuals who lack formal credit histories.

In addition, DCPs use real-time analytics to monitor borrower behaviour after loan disbursement and to identify potential fraud or emerging risk signals at an early stage for example, SIM swaps or abrupt declines in mobile activity. These capabilities support rapid loan approval processes, risk-based pricing, and more responsive credit risk monitoring. By relying on predictive analytics,

DCPs can improve consistency in credit decisions, reduce human error, and accelerate decision-making, which is particularly important in high-volume lending environments (Frost et al., 2019).

Providers segment their customer base based on risk profiles and tailor products accordingly. Strategies include offering higher amounts and longer tenures to repeat borrowers with good repayment history, diversifying across demographics, geography, and income levels to avoid concentration risk, Some DCPs integrate psychometric testing into onboarding to enhance segmentation accuracy (CGAP, 2020). To reduce delinquency, DCPs employ behavioral techniques such as, reminder SMS with payment due dates, gamification or rewards for timely repayment, repayment nudges based on borrower habits (e.g., reminding users on payday). These tactics leverage behavioral economics principles to positively influence repayment behavior (Bastin et al., 2021).

To address multiple borrowing and improve visibility of borrower exposure, DCPs are increasingly required to submit borrower data to credit bureaus, access external credit information to assess creditworthiness. In Kenya, DCPs licensed by the Central Bank of Kenya (CBK) must submit both positive and negative credit information to licensed CRBs (CBK, 2024).

Compliance with consumer protection regulations is vital for credit risk mitigation. Effective internal controls include caps on loan sizes and interest rates, transparent loan terms, fair debt collection practices, KYC and AML/CFT compliance mechanisms. Strong governance helps reduce operational risk and reputational damage, both of which are linked to credit risk exposure (World Bank, 2022).

## 1.2 Problem Statement

Section 1.1 provided an overview of Digital Credit Providers (DCPs), highlighting their growing contribution to financial inclusion and the credit risk management strategies employed to support digital lending activities. Despite their significant role in expanding access to financial services, DCPs operate in an inherently high-risk lending environment. Unlike conventional lending institutions such as commercial banks and microfinance institutions that often rely on collateral and other forms of security, digital credit providers primarily extend unsecured loans through technology-driven platforms. Consequently, digital lending is exposed to elevated levels of credit

risk, compounded by an increasingly stringent regulatory environment aimed at strengthening consumer protection and promoting responsible lending practices (CBK, 2024).

Empirical evidence suggests that digital credit providers encounter several challenges in effectively managing credit risk. Studies by Maina and Njeru (2023) and GSMA (2022) indicate that the ease of access to digital credit and the availability of multiple borrowing channels have contributed to increasing levels of over-indebtedness among borrowers, thereby heightening the likelihood of loan default. Furthermore, concerns regarding data quality, privacy, and the ethical use of alternative data sources continue to pose significant challenges to credit assessment processes, raising questions about accuracy, transparency, consent, and fairness. The absence of comprehensive credit histories among many first-time borrowers further complicates risk evaluation and contributes to elevated default rates. In addition, weaknesses in regulatory oversight, consumer protection mechanisms, and systemic risk management create further vulnerabilities within the digital lending ecosystem.

Notwithstanding these challenges, advances in financial technology present significant opportunities for strengthening credit risk management among digital credit providers. Emerging innovations in digital lending are transforming how lenders assess, monitor, and mitigate risk (Omokhoa et al., 2024). These developments include the adoption of advanced credit scoring models supported by shared digital identities, artificial intelligence-driven underwriting systems capable of detecting fraud and behavioral anomalies, blockchain-enabled borrower records that enhance transparency and reduce information asymmetries, and open finance frameworks that facilitate broader access to credit information across institutions. Collectively, these innovations have the potential to improve the accuracy, efficiency, and inclusiveness of credit risk management practices within the digital lending sector.

Against this backdrop, digital credit providers in Kenya face the dual challenge of managing heightened credit risk while simultaneously complying with increasingly demanding regulatory requirements. Their ability to respond effectively to these pressures is likely to be influenced not only by the availability of technological solutions but also by internal organizational characteristics. Factors such as governance structures, firm size, managerial expertise, resource availability, operational capacity, organizational culture, and staff competencies may significantly shape the adoption and effectiveness of credit risk management strategies. Understanding these

organizational factors is particularly important because they determine an institution's readiness to embrace innovation, implement appropriate risk controls, allocate resources efficiently, and respond to regulatory expectations. Consequently, variations in organizational characteristics may explain why some digital credit providers adopt more sophisticated and effective risk management practices than others. This study therefore sought to identify the credit risk management strategies prioritized by Digital Credit Providers in Kenya, examine the organizational factors influencing the adoption of these strategies, and evaluate management perceptions regarding their effectiveness. By addressing these issues, the study contributes to a deeper understanding of how organizational capabilities can enhance credit risk management and support the long-term sustainability and resilience of digital lending institutions.

## 1.3 Research Objectives and Research Questions

### 1.3.1 Research Objectives

The general objective of this study was to establish organizational factors influencing the prioritization of credit management strategies by digital credit providers in Kenya. More specifically:

1. To establish the credit management strategies prioritised by digital credit providers (DCPs) in Kenya
2. To establish the governance and financial factors influencing the credit management strategies by the DCPs.
3. To evaluate the DCPs' management perspectives on the relevance and effectiveness of these credit risk management priorities.

### 1.3.2 Research questions

The study therefore used the following research questions.

1. What are the credit management strategies prioritised by digital credit providers (DCPs) in Kenya?

2. What is the governance and financial organizational features influencing the use of the credit management strategies by the DCPs?
3. What are the DCP's management perspectives on the relevance and effectiveness of the priority credit risk management strategies?

## 1.4 Scope of the Study

The objectives of this study were to identify the credit risk management strategies prioritized by digital credit providers (DCPs) in Kenya, to determine the organizational factors influencing the adoption of these strategies, and to examine management perspectives regarding the various credit risk management approaches. The study focused on the 153 DCPs licensed by the Central Bank of Kenya as of December 2025, as presented in Appendix III. This focus is justified by the increasingly stringent regulatory requirements imposed by the Central Bank of Kenya on digital lending operations, including credit risk management practices. Primary data was collected through an online questionnaire administered to senior management of all licensed DCPs in the month of April 2026. A census approach targeting all senior management was adopted, as the population of 153 DCPs is relatively small and a low response rate was expected.

## 1.5 Significance of the Study

### 1.5.1 Regulators

For regulators like the Central Bank and others, the findings of the research provide information that will enable them to understand the nature of credit risk for DCPs, develop tools and models to assess credit risk, reduce predatory lending practices, new risks that may arise and hence develop appropriate guidelines to regulate DCPs.

### 1.5.2 Digital Credit Providers (DCPs)

The study's findings and conclusions assist DCPs in various ways, such as enabling better credit scoring using alternative data (e.g., mobile usage, transaction history), identifying key risk factors structuring loans to minimize non-performing loans, informing loan terms, pricing, and repayment

features tailored to borrower behavior, and preparing DCPs to meet regulatory standards on risk management and reporting.

### 1.5.3 Digital Credit Borrowers (DCBs)

Some digital credit borrowers will find the study useful in various ways. These include developing accurate credit scoring models, allowing more borrowers (especially the unbanked) to access loans fairly, data-driven risk assessment leading to risk-based pricing, reducing interest rates for low-risk borrowers, and guiding responsible lending limits, preventing borrowers from taking on excessive debt.

### 1.5.4 Researchers and Academicians

The results of this study are added to the empirical literature on credit risk management by digital credit service providers. The study provides insights into priority credit risk management strategies adopted by DCPs in Kenya and provides new research areas from the study's findings.

## 1.6 Chapter Summary

Chapter One presented the background to the study, beginning with an introduction to digital credit providers and subsequently examining credit risk management in the context of digital lending. The chapter also briefly highlights the research gaps, outlines the problem statement, and sets out the research objectives and questions, as well as the justification and scope of the study. Chapter Two provides empirical review, while Chapter Three outlines the methodology, Chapter Four the results and findings and Chapter Five provide the discussions and conclusions.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 Introduction

Chapter Two discusses the study's theoretical foundation and reviews the empirical literature upon which the study was grounded and which it seeks to advance. The chapter begins by outlining the theoretical framework, followed by a review of relevant empirical studies. It then summarizes the knowledge gaps identified in the literature, presents the conceptual framework, and concludes with the operationalization of the study variables.

## 2.2 Theoretical Framework

This study has adopted two theories: Resource-Based View (RBV), which focuses on explaining the adoption of financial access strategies as an innovation and Prospect Theory (PT), which aims to focus on how organizations can operate to serve the needs of various stakeholders, within the context of financial inclusion.

### 2.2.1 Resource-Based View Theory (RBV)

Risk management has increasingly shifted from a primarily compliance-driven function to a strategic priority. Contemporary organizations operate in environments marked by complex and interconnected risks, including financial volatility, cyber threats, reputational exposure, and frequent regulatory changes. Within this context, the Resource-Based View (RBV) provides a useful framework for explaining how firms can achieve sustainable competitive advantage through effective risk management. The RBV argues that superior and sustained performance is achieved when organizations acquire and deploy resources that are valuable, rare, difficult to imitate, and non-substitutable (VRIN) (Barney, 1991).

The Resource-Based View (RBV), as advanced by Barney (1991), underscores the strategic significance of internal organizational resources rather than external market positioning. In contrast to the industrial organization perspective, which emphasizes industry structure and other external determinants of performance, the RBV contends that firms can achieve superior performance by developing distinctive internal capabilities. Such capabilities may include

technological assets, human capital, organizational routines and processes, as well as intangible resources such as corporate culture and reputation.

Scholtens and Wensveen (2000) observe that, although financial intermediation (FI) theory is valuable for explaining how borrowers and lenders are linked within an economy, it has notable limitations. First, the theory tends to assume that financial institutions serve only an intermediary function, yet in practice they also perform broader roles, including risk management and contributions to social and economic development. Second, FI theory is largely grounded in the assumption of relatively static financial markets, despite the reality that financial systems are dynamic and continuously evolving. This dynamism implies that technological innovation can weaken or even bypass traditional intermediation roles.

From a risk management perspective, this view encourages a shift from reactive risk responses toward the development of strategic capabilities that allow organizations to proactively manage, mitigate, and potentially leverage risk for value creation (Wernerfelt, 1984). When integrated into organizational routines and decision-making processes, risk management capabilities can become strategic assets.

Enterprise Risk Management (ERM) systems provide organizations with an integrated and organization-wide perspective on risk, thereby improving coordination across functions and supporting more effective resource allocation (Gordon, Loeb, & Tseng, 2009). When designed to reflect a firm's specific operational realities and cultural context, ERM frameworks can be difficult for competitors to replicate, which positions them as potentially valuable, rare, inimitable, and non-substitutable (VRIN) resources.

Liebenberg and Hoyt (2003) further note that firms with dedicated risk management officers are more likely to adopt structured and strategically oriented approaches to managing uncertainty. Beyond reducing the likelihood and impact of adverse outcomes, such arrangements also allow firms to pursue value-creating but riskier opportunities with greater confidence. In this sense, risk management can enhance strategic flexibility and may be viewed as a key internal capability within the RBV framework.

A key contribution of the Resource-Based View (RBV) is its emphasis on human capital as a strategic resource. In the context of risk management, skilled professionals who can evaluate, interpret, and respond to complex risk scenarios strengthen an organization's overall capabilities.

In addition, a strong risk culture characterized by transparency, accountability, and ethical decision-making can improve an organization's ability to manage uncertainty effectively (Beasley, Clune, & Hermanson, 2005).

Nevertheless, RBV has important limitations. Some scholars argue that it places insufficient emphasis on external factors such as market disruptions or regulatory shifts, which may undermine even well-developed internal capabilities (Priem & Butler, 2001). Moreover, investments in risk management do not automatically translate into competitive advantage unless they are strategically aligned with organizational goals and tailored to the firm's specific context.

In recent empirical literature, the Resource-Based View (RBV) has been explicitly applied to credit risk management by regarding CRM mechanisms as strategic internal resources that are valuable, rare, inimitable, and non-substitutable (VRIN). For instance, Otieno et al. (2016), in a panel GMM study of Kenyan microfinance banks (2011-2015), conceptualize portfolio at risk (PAR) systems and loan-loss provisioning as internal capabilities under RBV; their regression results show these resources are significantly correlated with performance metrics like Return on Assets (ROA) and ROE (Return on Equity). Similarly, Esteve-Pérez and Mañez-Castillejo position bank-specific determinants such as capital buffers, asset quality monitoring, and management efficiency as VRIN-type internal resources whose development reduces credit risk and enhances long-term financial sustainability (2023).

### 2.2.2 Prospect Theory (PT)

Understanding how individuals and organizations make decisions under conditions of risk and uncertainty is central to the study and practice of risk management. Prospect Theory, developed by Kahneman and Tversky (1979), provides an influential framework for explaining decision-making behavior in such contexts. The theory suggests that individuals assess outcomes relative to a reference point often the status quo rather than in absolute terms. It also highlights the concept of loss aversion, whereby losses are experienced more intensely than equivalent gains are valued (Kahneman & Tversky, 1979).

Within Prospect Theory, the value function is concave for gains, indicating risk-averse behavior when individuals expect positive outcomes, and convex for losses, suggesting a tendency toward risk-seeking behavior when faced with potential losses. Importantly, the function is steeper for

losses than for gains, reflecting the asymmetric way in which individuals perceive and respond to unfavorable versus favorable outcomes.

Prospect Theory provides useful insights into why individuals and organizations may adopt suboptimal risk behaviors. When faced with potential losses, decision-makers often become excessively risk-averse, which can result in overly conservative strategies and missed value-creating opportunities. Conversely, when decisions are framed in terms of losses, they may engage in risk-seeking behavior to avoid realizing losses, for example, by continuing to commit resources to underperforming projects or investments (Barberis, 2013).

Recognizing these behavioral tendencies is important for risk management practice, as it allows risk managers to design governance arrangements, policies, and incentive structures that better align risk-taking behavior with organizational objectives. For instance, firms experiencing performance shortfalls may assume greater financial or operational risks in an attempt to recover losses, a pattern consistent with behavioral concepts such as the "house-money effect" (Thaler & Johnson, 1990). In such circumstances, effective risk management requires the establishment of controls that reduce the likelihood of irrational escalation of commitment and promote disciplined decision-making.

Traditional risk assessment approaches often give limited attention to behavioral factors that influence decision-making under uncertainty. Integrating insights from Prospect Theory into scenario planning and stress testing can help organizations anticipate potentially irrational reactions by stakeholders, markets, or competitors during adverse conditions. This strengthens organizational preparedness and supports the development of contingency plans that are more responsive to real-world behavioral dynamics (Wakker, 2010).

A section of empirical research has also supported the relevance of Prospect Theory to risk-related decision-making. For example, Shefrin and Statman (1985) applied the theory to investor behavior in capital markets, particularly in explaining the disposition effect where investors tend to sell winning stocks more readily than losing ones, contrary to rational profit-maximizing assumptions. Similarly, Fiegenbaum and Thomas (1988) applied Prospect Theory to strategic management, showing that firms performing below their reference groups are more likely to engage in higher levels of strategic risk-taking.

While Prospect Theory has proven useful, it has limitations. It is descriptive, not prescriptive, and does not specify how decisions should be made to optimize outcomes. Additionally, the theory assumes static reference points, whereas in practice, reference points may shift over time or vary between stakeholders (Schmidt & Zank, 2012).

Empirical evidence increasingly shows that Prospect Theory offers valuable behavioral insight into credit risk management, especially in banking contexts. Trichilli, Kharrat, and Boujelbène (2021) demonstrate that both Islamic and conventional banks operating in the MENA region adjust their risk-taking based on returns relative to benchmarks: when performance falls below target, risk-taking intensifies, a direct reflection of loss aversion and reference-point dependence. At the corporate level, Kliger and Tsur (2011) observe in U.S. public firms that those underperforming relative to industry benchmarks pursue riskier strategies, while those outperforming act conservatively, further endorsing Prospect Theory as a tool to explain corporate risk behavior under financial distress.

## 2.3 Empirical Studies

This section provides a preview of previous studies on the use of various credit risk management strategies by lenders, narrowing down to digital credit lending, factors that will likely influence the prioritization of credit risk strategies and management perspectives on credit risk management strategies.

### 2.3.1 Empirical studies on credit risk management strategies by digital lenders

Björkegren and Grissen (2017) present evidence from a South American digital lender that operates through a telecommunications platform. Their findings indicate that mobile phone usage indicators, particularly calling patterns, can predict default risk more effectively than conventional credit bureau information, especially for borrowers with limited formal financial histories. This suggests that alternative digital data sources can strengthen credit risk assessment among digitally excluded populations (Björkegren & Grissen, 2017).

Using a descriptive survey of selected digital lending firms in Kenya, Gideon et al. (2021) examine how risk assessment practices relate to financial sustainability. Although their analysis does not

show a statistically significant relationship between overall risk management practices and sustainability, the study highlights persistent weaknesses in creditworthiness evaluation. Specifically, many firms were found to rely on inadequate assessment mechanisms, charge relatively high interest rates, and face elevated levels of default. The authors therefore recommend improving credit scoring methods and reducing interest rates as measures that may help lower default rates (Gideon et al., 2021).

Maina and Njeru (2023) survey all 32 registered digital credit providers in Kenya, investigating how credit procedures, appraisal, monitoring, and recovery systems impact loan recovery performance. They find significant and strong positive correlations between each credit risk practice and recovery rates (e.g., $r = 0.438$ for credit procedures, $r = 0.351$ for credit monitoring). Their regression model explains 77.4% variance in performance. They conclude that robust credit procedures and monitoring systems significantly enhance repayment outcomes in digital lending environments (Maina & Njeru, 2023).

Yun (2025) examines how the rise of fintech, big data, and artificial intelligence is reshaping credit risk management, highlighting both opportunities and challenges for lenders in the digital age. The study emphasizes that digital lending platforms increasingly rely on alternative data sources and algorithmic credit scoring, which can expand financial inclusion but also introduce risks such as model bias, data privacy concerns, and regulatory gaps. Yun outlines challenges, including cyber threats, over-indebtedness, and the difficulty of monitoring rapidly growing digital loan portfolios. To address these, the paper proposes solutions such as enhancing regulatory frameworks, adopting robust data governance standards, integrating explainable AI in risk models, and fostering collaboration between fintechs, traditional financial institutions, and regulators. Overall, the study underscores that sustainable digital credit risk management requires balancing innovation with consumer protection and systemic stability.

Although their analysis is not restricted to digital-only lenders, Allya et al. (2025) investigate the relationship between FinTech adoption and non-performing loans (NPLs) among 30 commercial banks in Tanzania over the period 2010 - 2021. Using a system GMM approach, they report that higher levels of FinTech integration are associated with significantly lower NPL ratios, with the effect being particularly pronounced among smaller banks. These findings suggest that digital tools

such as automated credit scoring systems and mobile lending platforms can enhance credit risk management outcomes when effectively implemented (Allya et al., 2025).

Overall, the literature indicates that credit risk management practices among digital credit lenders, especially credit appraisal procedures, borrower monitoring mechanisms, and recovery frameworks, have a direct influence on loan performance and institutional sustainability. While some providers achieve better outcomes through structured and robust systems, others continue to face elevated default rates due to weaknesses in their risk management processes. In addition, the adoption of FinTech tools and alternative data-driven credit models appears to strengthen predictive accuracy and reduce loan losses.

For this study therefore, credit risk management strategies were categorized into four broad areas, i.e. dynamic credit scoring models, loan structuring and credit limits, partnerships and credit guarantee arrangements, and automated collection mechanisms and early warning systems.

### 2.3.2 Empirical studies on organizational factors influencing the use of credit risk management strategies by lenders

Several empirical studies have examined risk management practices among digital lenders from a broader governance perspective. Ferilli (2024), together with related evidence from the finance literature, suggests that firms with stronger formal governance arrangements, such as active board oversight, dedicated risk committees, and experienced senior management, are more likely to adopt conservative risk appetites and implement structured risk controls as they scale fintech products. Importantly, these relationships remain robust even after accounting for firm size and market conditions.

Similarly, cross-country archival research on fintech development and bank risk indicates that institutions operating in jurisdictions with more mature governance systems and stronger institutional pressures tend to invest more heavily in monitoring mechanisms, fraud controls, and data governance frameworks. Collectively, these findings suggest that governance functions both as an enabling mechanism by directing organizational resources toward risk management and as a disciplining force that reduces incentives for excessively risky product design and weak control environments. According to Gambacorta et al. (2024) and Sun (2024), IT & data capabilities,

analytic talent, access to alternative digital data, secure IT operations and machine-learning models as the technical backbone for modern risk-management practices.

The quality of organizational culture, including risk-aware mindsets, transparency, and management support, strongly influences risk management adoption. In Zimbabwean banks, culture emerges as a key predictor of ERM uptake superior risk culture correlates with higher adoption likelihood. More broadly, studies show that stakeholders like regulators and societal norms shape risk culture and thus indirectly influence adoption decisions (Kanhai & Ganesh, 2014).

Size and structural complexity of institutions also matter. Banks with larger size and more diversified operations are more likely to adopt credit risk systems and ERM frameworks. Mandimutsira (2015) finds that in Zimbabwe, governance (board size and presence of credit risk committee) Bank size, complexity, leverage, and asset opacity are important determinants in ERM adoption among banks. In Ghana and South Africa, insurers with greater industrial diversification and complex operations demonstrate significantly higher ERM adoption rates.

External institutional factors also affect adoption. Firms audited by Big Four audit firms tend to adopt ERM more often, possibly due to audit quality expectations and professional guidance. Ownership structure also matters: some studies indicate that firms with broader or institutional ownership are more likely to implement robust risk frameworks to protect stakeholder value (Shlash, 2025).

Organizational capacity in terms of human resources, training, and technology is crucial for risk management adoption. Effective human resource efficiency, training, and appropriate IT infrastructure enhance adoption and implementation of risk systems. Organizations with greater capacity invest in training employees on risk processes and adopting supportive technologies, improving accessibility and consistency of risk practices (Okello, 2012).

Adoption of credit risk management and ERM by credit-providing institutions is influenced by a constellation of organizational factors. Governance strength (presence of credit risk committee), culture, firm size, firm performance and complexity, external audit and ownership, as well as human resources and digital capacity, jointly shaped institutions' willingness and ability to implement structured risk frameworks. Scholars and practitioners designing interventions should

tailor approaches to institutional contexts, ensuring that organizational readiness aligns with regulatory and strategic demands (Shnoise, 2025).

### 2.3.3 Empirical studies on the perspectives of Management credit management strategies

Owners and senior management significantly shape an institution's approach to credit risk management (CRM). Their attitudes, incentives, and governance decisions influence credit policies, oversight mechanisms, and risk damping strategies.

Ntiamoah et al. (2019) conducted a mixed-method study involving management and staff of Ecobank, Ghana Commercial Bank, and Stanbic Ghana. Using questionnaires and interviews, they found a strong positive correlation between management attitudes and effective CRM adoption. Bank managers who viewed credit risk control as a strategic priority were significantly more likely to implement robust credit review processes and enforcement policies (Ntiamoah et al., 2019).

Leora Klapper and colleagues (Cole et al.2020) examined loan officers' behavior under different incentive schemes funded by bank owners. They found that high-powered incentives like performance-based pay led to more thorough risk screening, improved detection of poor credit, and higher per-loan profitability. Conversely, volume-based incentives reduced screening effort and performance quality. Delaying incentive payouts dampened risk-taking and improved long-run screening quality (Cole et al.2020).

Empirical evidence underscores that management attitudes and owner-level incentive structures shape the effectiveness of credit risk management. Leaders' framing of credit risk how it is governed, incentivized, and monitored directly influences how well credit systems function.

## 2.4 Summary of Empirical Studies and Research Gaps

Section 2.3 has provided empirical studies that relate to the use of credit risk management strategies, factors that influence the adoption of the priority credit risk management strategies and management perspectives on the effectiveness as well as other perspectives on credit risk management strategies. Table 2.1 provides a highlight of the studies and the research gap being addressed by the current study.

**Table 2.1 Summary of Empirical Studies and Research Gaps**

| Author(s) | Study focus | Methodology | Findings | Research gap filled |
|---|---|---|---|---|
| Bjorkegren & Grissen (2017) | General risk management practices by digital credit lenders in South Africa | Logistic regression / stepwise logistic model on a sample included about 7,068 subscribers who moved from prepaid to postpaid under relatively permissive credit criteri | The study suggests that mobile-phone behavior metadata provide a powerful alternative (or supplement) to traditional credit bureau information, especially for populations that lack formal financial histories | Focused on general risk management strategies in South Africa. The current study aims to focus on credit risk and is situated in Kenyas Digital credit providers. |
| Gideon et al. (2021) | Credit risk management and financial sustainability of digital lending firms in Kenya. | Case study approach that combined structured questionnaires and interviews with managers of selected digital lenders (5) | Robust credit risk management practices are critical for the long-term sustainability of digital lending firms in Kenya, given their reliance on unsecured, short-term credit products and high exposure to default risk | The study only focused on 5 digital lenders before the new digital credit guidelines issued by the Central Bank of Kenya in 2022. |
| Maina and Njeru (2023) | The effect of credit risk management practices on loan recovery performance among registered | The study targeted managers of licensed digital lenders, collecting data through structured questionnaires and analyzing it with both descriptive and | The findings revealed that key credit risk management practices—such as stringent borrower appraisal, | The study focused on only 20 credit providers and emphasized loan recovery, while the current study |

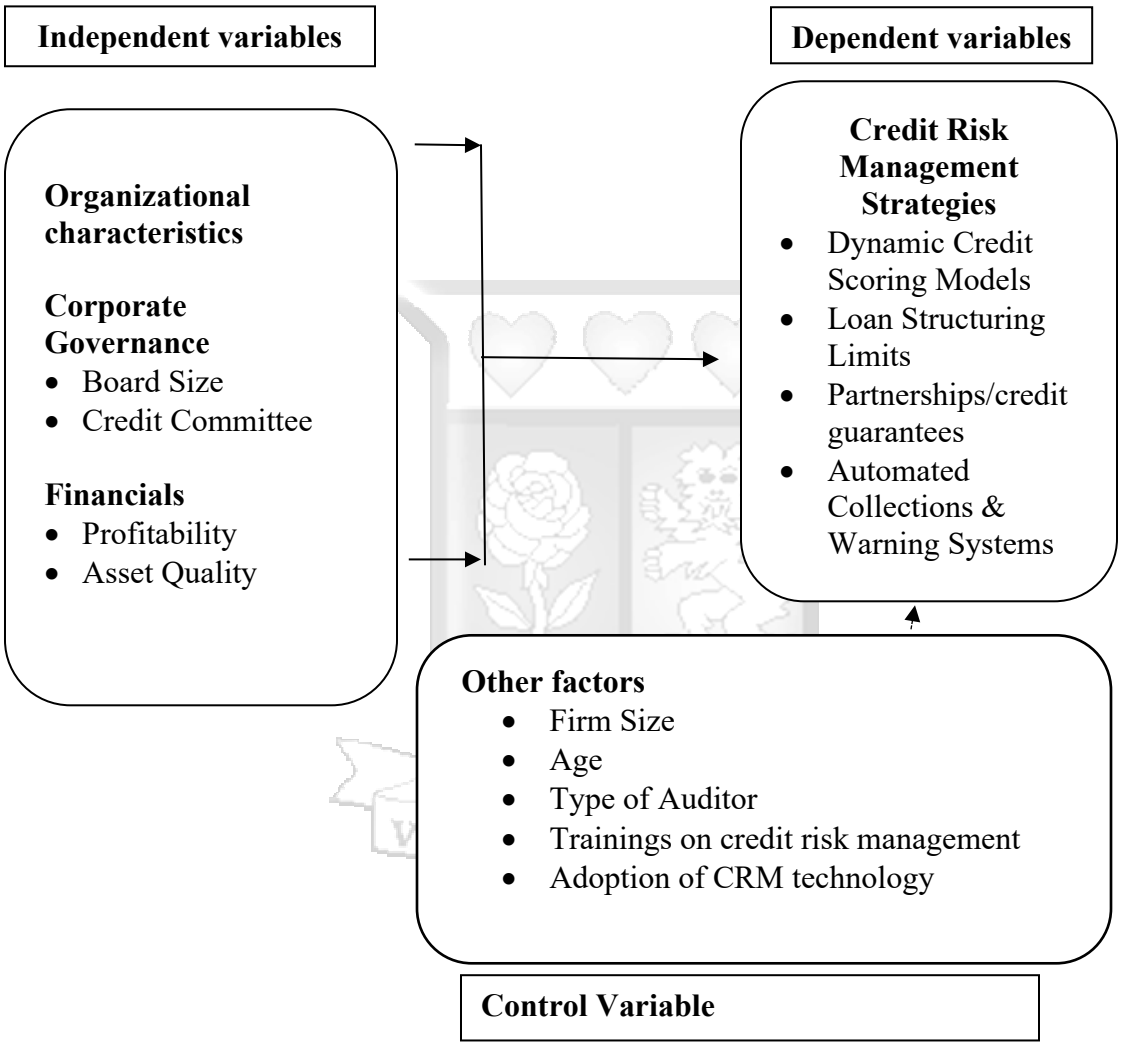
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| | digital credit providers in Kenya. | inferential statistics, including regression analysing | effective loan monitoring, use of credit scoring models, and well-structured collection strategies—had a significant positive effect on loan recovery performance | has expanded the digital providers as well as their credit risk management practices. |
| Yun (2025) | Trace how credit risk management has evolved under digital disruption | A literature review approach that synthesizes existing academic and industry sources, examining emerging technologies such as big data, artificial intelligence/machine learning, and blockchain, and comparing these with traditional methods including credit scoring and analysis of financial statements. | The paper concludes that while digital risk-management techniques offer promising improvements; to fully realize their potential the sector must strengthen governance, ethics, fairness, and regulatory oversight. | Paper focuses on review methodology, while the current study aims to obtain empirical evidence on the factors that influence the use of credit risk management techniques. |
| Kanhai and Ganesh, 2014). | The factors influencing the adoption of enterprise risk management (ERM) among insurers in Ghana and South Africa. | Data were gathered using structured questionnaires administered to risk managers, senior executives, and other relevant bank officials, and the responses were analysed through descriptive statistics and regression analysis. | The authors concluded that strong leadership commitment and regulatory enforcement are critical to deepening ERM adoption in Zimbabwe's banking sector. | The study focused on general ERM in banks, while this study focuses on credit risk and more specifically for digital lenders. |
| Mandimutsira (2015) | The factors influencing the adoption and implementation | A case study–based investigation where primary data were collected through | The study concluded that successful ERM implementation | The study focused on general ERM in banks, while |

| | | | | |
|---|---|---|---|---|
| | of enterprise risk management (ERM) by banks in Zimbabwe | structured questionnaires and interviews with bank executives, risk officers, and regulators, while secondary data were drawn from policy documents and industry report | in Zimbabwe's banking sector requires stronger regulatory frameworks, capacity building, and greater integration of ERM into corporate strategy. | this study focuses on credit risk and more specifically for digital lenders. |
| Shlash (2025) | What an internal audit governance factors influence the adoption of risk-based auditing in Jordanian commercial banks. | Data were collected through structured questionnaires distributed to internal auditors, audit committee members, and risk managers, and the responses were analyzed using statistical techniques such as regression analysis to test the relationships between governance factors and risk-based auditing adoption. | The study concluded that strengthening internal audit governance structures is essential for enhancing risk-based auditing practices and improving risk management effectiveness in Jordan's banking sector. | The study focused on risk-based auditing, while the current study extends to credit risk management. |
| Shnoise (2025) | The determinants of enterprise risk management (ERM) adoption among insurers in Ghana and South Africa | Used panel data from 2015 - 2018 and applied both panel logistic regression and quantile regression analysis to capture variations across different levels of ERM adoption | Overall, the study concluded that ERM adoption is influenced not only by firm characteristics but also by the intensity of adoption, with drivers varying across different adoption stages. | The study was based on general ERM, and therefore, the current study narrows down to credit risk management and digital credit providers. |

## 2.5 Conceptual Framework

Figure 2.1 illustrates the independent and dependent variables that the study will examine. Consistent with prior research, organizational size is included as a control variable.

**Figure 2.1 The Conceptual Framework**



## 2.6 Operationalisation of the Variables

Table 2.2 presents the criteria used to operationalize the study's independent, control, and dependent variables. It outlines the measurement indicators, supporting empirical studies, relevant theoretical foundations, and the proposed tests of the variables.

**Table 2.2 Table of Operationalization of Variables**

| Variable | Measurement of Variable | Supporting Past Studies | Supporting Theories | Data Source | Analysis |
|---|---|---|---|---|---|
| **Dependent Variables** | | | | | |
| Credit Risk Management Strategies | Ranking by the organization:<br>• Dynamic Credit Scoring Models<br>• Loan Structuring Limits<br>• Partnerships/credit guarantees<br>• Automated Collections & Warning Systems<br>(5 Point Likert Scale) | Maina and Njeru (2023) | RBV and PT | Questionnaire | Descriptive and Multivariate |
| **Independent Variable** | | | | | |
| Corporate Governance – | • Board Size | Mandimutsira (2015) | RBV | Questionnaire | Regression Analysis |
| Profitability | • ROE (Profit after tax/Equity) | Mandimutsira (2015) | RBV | Questionnaire | Regression Analysis |
| Asset Quality | • Proportion of Performing Loans | Mandimutsira | RBV | Questionnaire | Regression Analysis |
| Other aspects - Age | • Number of years in operation | Okello (2012) | RBV | Questionnaire | Regression Analysis |

| | | | | | |
|---|---|---|---|---|---|
| Other aspects - Type of Auditor | 1 for big 5 and 0 for Non big five | Shnoise (2025 | RBV | Questionnaire | Regression Analysis |
| Other aspects - Trainings on credit risk management | Number of Trainings conducted on Credit Risk management annually | Shnoise (2025) | RBV | Questionnaire | Regression Analysis |
| Other aspects - Adoption of CRM technology | Number of technologies adopted for CRM | Cole et al. (2020 | RBV | Questionnaire | Regression Analysis |
| **Control variable** | | | | | |
| Size | • Log of Total Assets | Mandimutsira (2015) | RBV | Questionnaire | Regression Analysis |

**(Source: Author)**

**FI – Resource-Based View Theory**

**PT – Prospect Theory**

## 2.7 Summary of the Chapter

Chapter Two presented the study's theoretical foundation, drawing on the resource-based view theory and prospect theory. It also reviewed empirical studies relevant to the research, outlined the conceptual framework, and explained the operationalization of the study variables. Chapter Three follows, focusing on the research methodology.

# CHAPTER THREE: RESEARCH METHODOLOGY

## 3.1 Introduction

Chapter Three presents the methodological framework adopted in this study, outlining the research philosophy and research design that guide the overall inquiry process. The chapter further describes the target population, sampling techniques, and the procedures employed in data collection and analysis to ensure systematic and objective investigation of the research problem. In addition, it discusses the measures undertaken to ensure validity and reliability of the research instruments and concludes by addressing the ethical considerations observed throughout the study.

## 3.2 Research Philosophy

Research philosophy provides the values and assumptions that guide the process of scientific research. It forms the foundation of knowledge on which the underlying predispositions of a study are based (Mugenda & Mugenda, 2003). It explains the development of knowledge and the nature of knowledge (Creswell, 2009). The major research philosophies are positivism and post-positivism.

Positivism is concerned with uncovering the truth and presenting it by empirical means (Henning et al., 2004). The positivistic philosophical foundation is based on real facts, objectivity, neutrality, measurement, and validity of results (Saunders et al., 2009). Its fundamental tenets are that true knowledge is derived from sensory experience and may be discovered via experimentation and observation, and that reason and observation are useful in comprehending human behavior. Positivists adhere to realism, which holds that knowledge is both objective and quantitative and that reality is provided as given and is measurable using attributes that are independent of the researcher and the research tools. Post-positivist philosophy believes that people have subjective experiences of the external world. They believe that reality is socially constructed. According to Myers (2009), postpositivist scholars begin with the idea that social creations like shared meanings, languages, and consciousness are the only ways through which reality can be accessed. The observation and interpretation processes underpinning the subjective paradigm entail collecting data on events and deriving meaning from that data through the application of largely subjective assumptions.

This study was anchored mainly on a positivist philosophical approach (for the first two objectives) and minimally, on post-positivism, for the third objective, which obtained the subjective views of the digital credit providers on credit risk management strategies.

## 3.3 Research Design

Research design recommends the collection and analysis of data with the aim of conducting the research efficiently (Kothari, 2004). The issues of sampling tactics, data collection tools, and data gathering protocols are all addressed by research design. For this study, a mixed method research technique that combines quantitative and qualitative methodologies will be employed. The mixed approach focuses on research questions that need an examination of multiple levels of perspective, cultural influences, and contextual understandings from daily life. Creswell and Tashakkori (2007), note that mixed methods are a deliberate use of rigorous qualitative research to explore the meaning and comprehension of the constructs and rigorous quantitative research to assess the quantity and frequency of constructs. The intention is to establish a thorough interpretive framework that can lead to fresh insights into the problem or potential solutions by combining the benefits of both types of data collection approaches. Thus, this inquiry employs both quantitative and qualitative methodologies. The study used concurrent mixed methods as both the qualitative and quantitative data will be collected and analyzed concurrently (Creswell & Tashakkori, 2007). Both quantitative and qualitative data were collected from the online questionnaire.

## 3.4 Population and Sampling

A population is an entire set of individuals or objects having a common observable characteristic about which a researcher is interested in (Sekaran & Bougie, 2016). The study used the digital credit providers licensed by the Central Bank of Kenya as at end of September 2025. The list is provided in Appendix III and is also available in the Central Bank of Kenya Website. Due to the smaller population of 153, the study will use a census.

## 3.5 Data Collection and Tools

The study collected primary data using a semi-structured questionnaire that included information about the organization and additional variables. The questionnaire was structured, and the

questions were a mixture of yes/no, different levels of the Likert Scale, structured and unstructured, with open-ended questions. The questionnaire was administered online.

## 3.6 Data Analysis

In achieving objective one, the research used descriptive analysis to measure the ranking of various credit risk management strategies as per the Likert scale in the questionnaire. This ranking provided the dependent variable in the second objective. The second objective incorporated both descriptive and multivariate analysis.

The focus of data analysis in this study was to establish the influence of organizational factors in ranking priority risk management strategies. The independent variables are grouped into corporate governance variables (board size and presence of credit risk committee), Financials (Profitability as per ROE and asset quality), Age, Type of Auditor, CRM trainings, CRM technologies and Size (TA).

Given that the credit risk management strategies take a ranking status based on a Likert scale, a multinomial logistic regression model was. This model applies when the dependent variable can take a discrete status (Binary number), and the independent variables are a combination of continuous and dichotomous variables (Gujarati, 2011). The model was provided as follows:

$$\text{Log } (P/1\text{-}P) = \alpha_i + ß_1BS + ß_2CM + ß_3ROE + ß_4AQ + ß_5AGE + ß_6AUD + ß_7CRMTR + ß_8CRMTE + ß_9FSIZE$$

The symbols represent the following variables

**Table 3.1: Summary of variables in the regression model**

| Coefficient | Symbol | Variable |
|---|---|---|
| Log (P/(1-p) | | The dependent variable is adjusted and measured as log likelihood in the multinomial logistic regression. |
| α | | Constant |
| $ß_1$ | BS | Board Size |
| $ß_2$ | CM | Credit Committee |
| $ß_3$ | ROE | Return on Equity |

| | | |
|---|---|---|
| ß4 | AQ | Asset Quality |
| ß5 | AGE | Age |
| ß6 | AUD | Type of Auditor |
| ß7 | CRMTR | Credit Management Trainings |
| ß8 | CRMTE | Credit Management Technologies |
| ß9 | FSIZE | Firm Size |

For the third objective, the responses were analyzed using descriptive statistics, while some of the responses, especially unstructured, will be presented in themes. The relevant software for both descriptive and multivariate analysis will be SPSS version 29.

For the multivariate regression model, detailed diagnostics are discussed in chapter four with the results and findings. However, according to Gujarati (2011), the model fit for multinomial logistic regression can be conducted at various levels. First, the mean dependent variable describes the outcome of a stochastic event with a density function (a function of cumulated probabilities ranging from 0 to 1). A cut point (e.g., 0.5) can be used to determine which outcome is predicted by the model based on the values of the predictors.

Secondly, Pseudo–R–squared is the Cox and Snell's R-Square that imitates multiple R-Square based on 'likelihood', but its maximum can be (and usually is) less than 1.0, making it difficult to interpret. Thirdly, the likelihood ratio chi-square is used to evaluate if the logistic model is better than a model with no predictors, i.e. a null model. A model with a p-value < 0.001 indicates that the model fits significantly better than a null model.

Finally, the Akaike Information Criterion (AIC) is a quantitative measure used to assess the goodness-of-fit of a logistic regression model to the data from which it is estimated. In statistical analysis, AIC facilitates comparison across alternative candidate models to sidentify the model that best balances explanatory power and parsimony. Under the AIC framework, the preferred model is the one that accounts for the greatest variation in the outcome while using the fewest independent variables. Generally, lower AIC values indicate a better-fitting model relative to competing specifications.

## 3.7 Research Quality

Research quality aims at enhancing the credibility of the study. Quality considers both the validity and reliability of the collected data. Validity is the extent to which the research measures what it aims to measure (Creswell, 2014). On the other hand, reliability ensures the consistency of the results over time and with different researchers (Mohajan, 2017). In this study, a combination of qualitative and quantitative research methods was employed to increase the validity and reliability of the findings. Structured questions provided more standardized and generalizable data. To establish the validity of the questionnaire, content validation was done to verify that the questions asked answered the questions and will meet the study's objectives. (Taherdoost, 2016).

To achieve reliability of the questionnaire, the questionnaire was pilot tested to assess its reliability using Cronbach's Alpha before being finally administered. Cronbach's alpha is a measure used to assess the reliability, or internal consistency, of a set of scale or test items (Taber, 2018). In other words, the degree to which a measurement is consistent with itself is referred to as its reliability. Cronbach's alpha, which is a number between 0 and 1, can be used to gauge the degree of consistency in a measurement. The higher the Cronbach's Alpha, the more reliable the questionnaire is, which is usually 0.7. Cronbach's alpha was tested on 15 DCPs from the pilot test in relation to the following Likert Scale Questions:

**Table 3.2: Cronbach's Alpha Test result on Likert Scale Questions**

| | **Observations** | **Alpha** |
|---|---|---|
| Credit Committee | 15 | 0.708481 |
| Type of Audit | 15 | 0.708477 |
| Credit risk management strategies | 15 | 0.708123 |
| Dynamic credit scoring practices | 15 | 0.724203 |
| Loan Structuring & Limits practices | 15 | 0.735861 |
| Partnerships/credit guarantees practices | 15 | 0.726113 |
| Automated Collections and Warning Systems | 15 | 0.727821 |
| Credit risk management strategies effectiveness | 15 | 0.778473 |
| Test Scale | | 0.702696 |

Overall, the Cronbach's alpha is 0.702696, which is slightly more than 0.7.

## 3.8 Ethical Considerations

Ethical matters are important to ensure that research is valid, while the rights of the various respondents are respected. During primary data collection from the respondents, high levels of confidentiality were observed to ensure that the outcomes represented the data that was examined. The respondents were given the option to participate willingly, with confidentiality maintained and as far as possible, keeping the participants anonymous. The proposal was submitted to the Strathmore Institutional Ethics and Scientific Review Committee (SERSRC) for ethical approval and will be the National Commission for Science, Technology, and Innovation (NACOSTI). See Appendix IV for the two ethical approvals. To avoid plagiarism, all scholars whose work was used in the study were cited and referenced.

## 3.9 Chapter Summary

This chapter presented the research philosophy (having more of positivism and less of post positivism), the research design (mixed concurrent mixed), the population (153 Digital Credit Providers), the data collection sources and tools (online administered questionnaire) and the data analysis (Both descriptive and multivariate, aided by the multinomial regression model). The chapter concluded with the research quality of reliability and validity and ethical aspects.

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# CHAPTER FOUR: FINDINGS AND RESULTS

## 4.1 Introduction

Chapter Three covered the research methodology of the study. Chapter four presents the findings and results. The findings and results are presented based on the questionnaire, with relevant descriptive and multivariate analysis and conclude with aspects relating to unstructured responses.

## 4.2 Respondents Demographics

### 4.2.1 Role in the organization

Figure 4.1 provides a summary of the titles of the respondents.

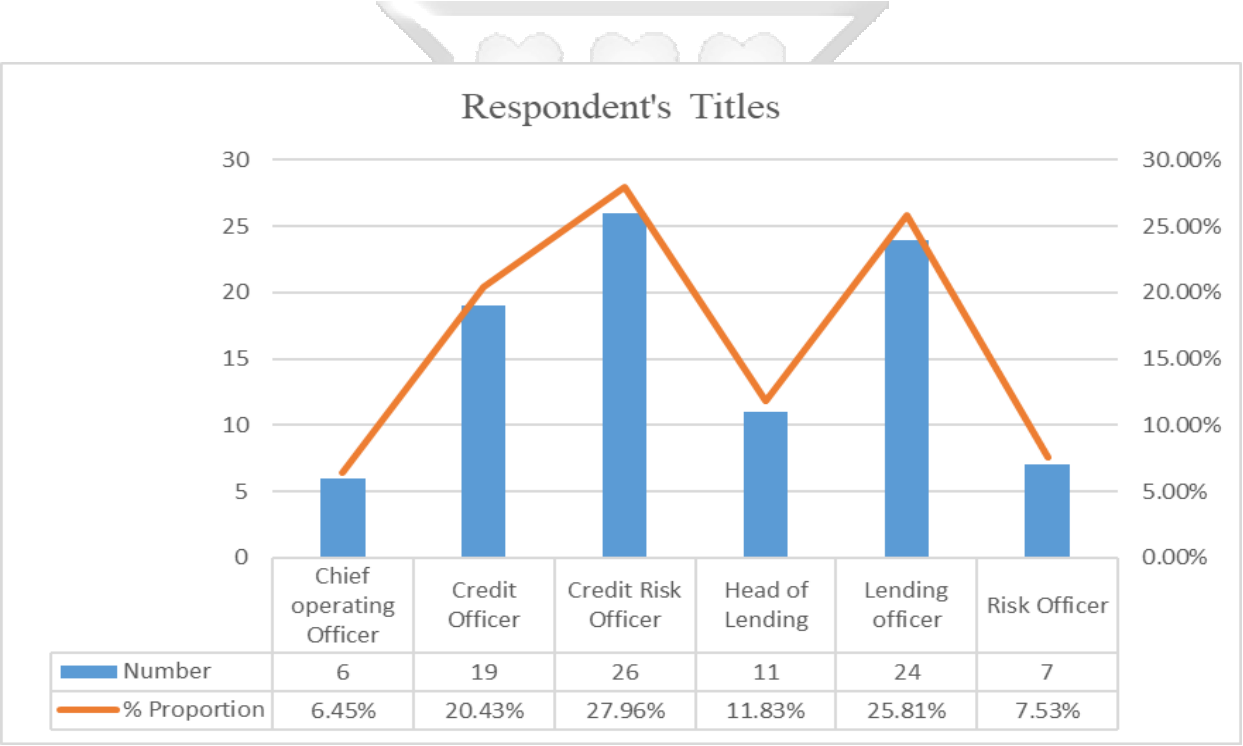



**Figure 4.1: Respondents' Titles**

### 4.2.2 Duration in the organization and industry experience

Table 4.1 provides a summary of the number of years in the organization as well as the number of years of work experience.

**Table 4.1: Descriptive Statistics for Respondents Years in the DCP and Industry Experience**

| Descriptive Statistics | Years in Org | Industry Experience |
|---|---|---|
| Mean | 5.612903226 | 7.892473118 |
| Standard Error | 0.293307085 | 0.438467721 |
| Median | 5 | 8 |
| Mode | 4 | 11 |
| Standard Deviation | 2.828551089 | 4.228429572 |
| Sample Variance | 8.000701262 | 17.87961664 |
| Kurtosis | -1.102202441 | -1.182215062 |
| Skewness | -0.001875603 | -0.087463263 |
| Range | 9 | 14 |
| Minimum | 1 | 1 |
| Maximum | 10 | 15 |

Overall, on respondents' demographics, the data indicates that respondents working in digital credit providers have moderate tenure within their current organizations, with an average of approximately 5.6 years and a median of 5 years. This suggests a workforce with relatively sufficient institutional familiarity. The low skewness (close to zero) implies that tenure is fairly evenly distributed, without significant concentration at extremes. Additionally, the moderate standard deviation reflects some variation in organizational tenure, indicating a mix of newer and more experienced employees within digital credit providers.

In terms of overall industry experience, respondents appear more seasoned, with a higher mean of about 7.9 years and a median of 8 years. This gap between organizational tenure and industry experience suggests that many employees may have transitioned across institutions within the digital credit sector, bringing accumulated expertise into their current roles. The presence of a mode at 11 years further highlights a subset of highly experienced professionals, while the wider range and higher standard deviation indicate greater dispersion in experience levels compared to tenure.

From a distributional perspective, both variables exhibit near-symmetrical distributions (skewness close to zero) and negative kurtosis, indicating relatively flat distributions with fewer extreme

outliers. Overall, the findings suggest that digital credit providers are staffed by a blend of moderately tenured employees and more experienced industry professionals, which is advantageous for balancing institutional knowledge with broader sector expertise in credit risk management practices.

## 4.3 Organizational Demographics

### 4.3.1 Number of years of existence

Table 4.2 provides a summary of the number of years DCP has been in operation

**Table 4.2: Descriptive Statistics for a DCP's years of operation**

| | |
|---|---|
| Mean | 6.612903226 |
| Standard Error | 0.293307085 |
| Median | 6 |
| Mode | 5 |
| Standard Deviation | 2.828551089 |
| Sample Variance | 8.000701262 |
| Kurtosis | -1.102202441 |
| Skewness | -0.001875603 |
| Range | 9 |
| Minimum | 2 |
| Maximum | 11 |

The data shows that digital credit providers have been in operation for an average of approximately 6.6 years, with a median of 6 years, indicating a moderately mature sector. The near-zero skewness suggests a balanced distribution of firms across different operational ages, while the relatively moderate standard deviation indicates some diversity in firm maturity. Overall, this implies a sector composed of both relatively new entrants and more established players, reflecting gradual industry growth and consolidation.

### 4.3.2 Board Size

Figure 4.2 provides details about the board size of the digital credit providers.

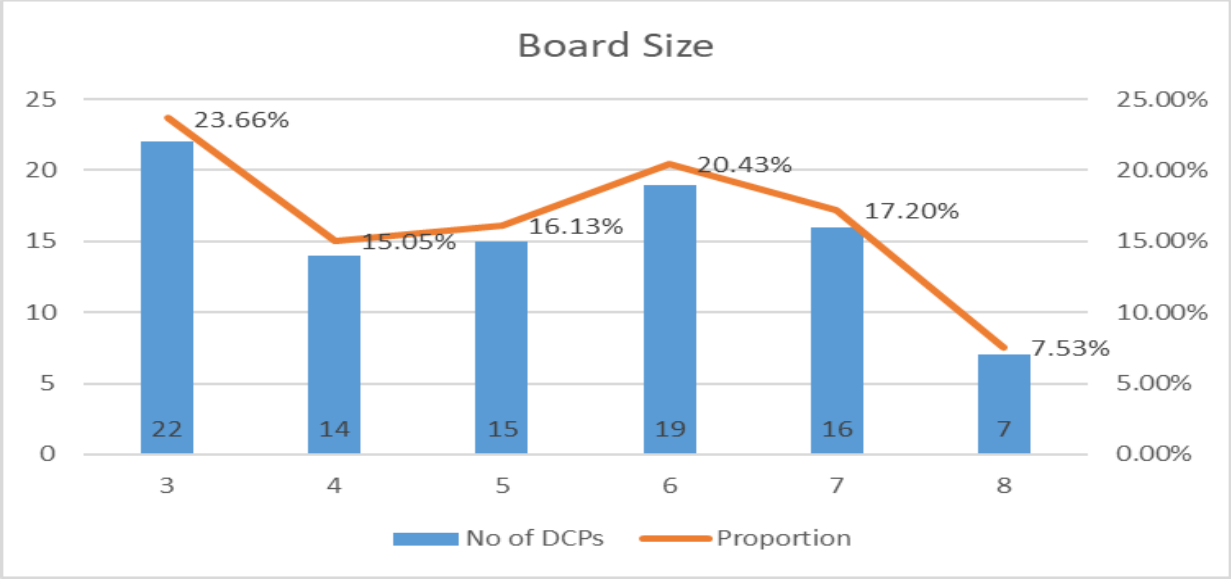



**Figure 4.2: Number of Board Members**

The figure on board size likely reflects variability in governance structures across digital credit providers. A spread in board sizes typically suggests differences in organizational complexity, with larger boards potentially indicating more formal governance frameworks, while smaller boards may reflect leaner, more agile decision-making structures for digital credit providers in Kenya.

### 4.3.3 Presence of a Board Credit Committee and Type of Auditor

Figure 4.3 provides a summary of the number of DCPs with a Credit Committee.

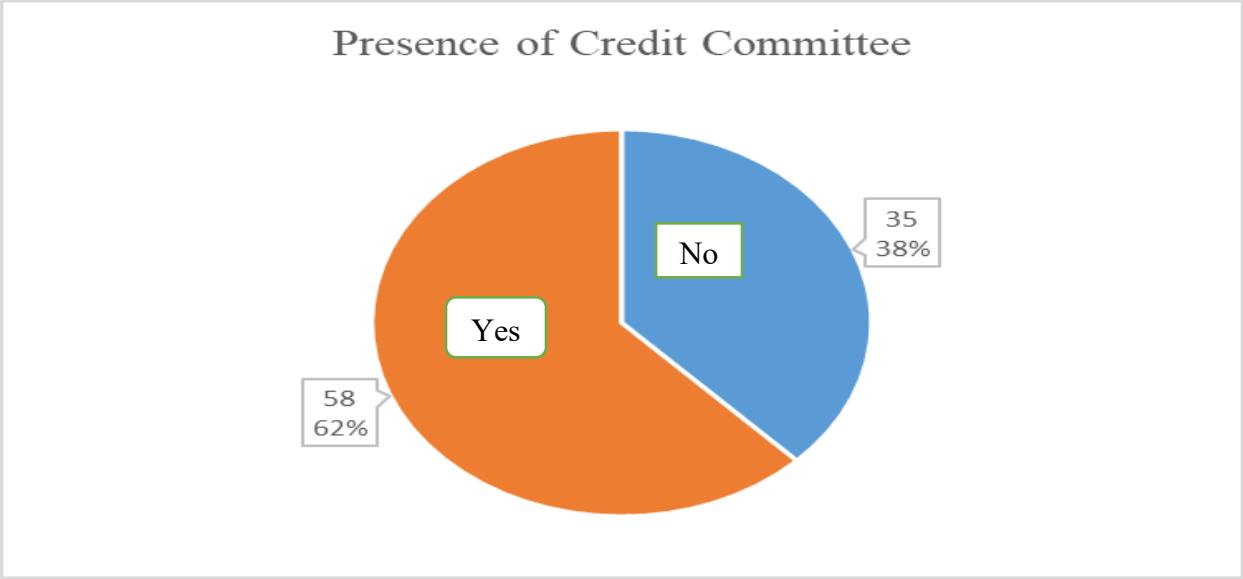



**Figure 4.3: Presence of a Credit Committee on the DCPs Board**

The summary of whether digital credit providers have a credit committee provides insight into governance and risk oversight practices. A higher proportion of DCPs with credit committees would indicate strong institutionalization of credit risk management, whereas a significant number without such committees may point to governance gaps or reliance on less formal risk management processes.

Figure 4.4 provides a summary of the digital credit providers that are audited by the Big Five audit firms.

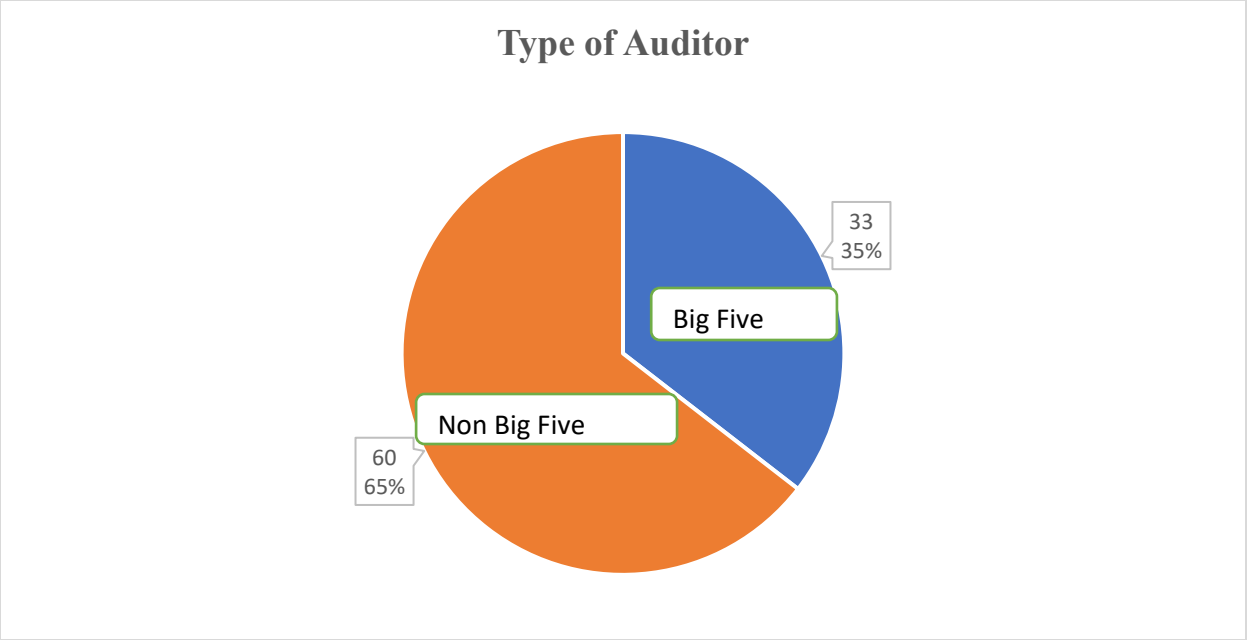



**Figure 4.4: DCPs that are audited by the Big Five Audit Firms**

A lower number of digital credit providers are audited by the audit firms not in the Big Five category, which could indicate a lesser adherence to high-quality financial reporting and governance standards, but may be explained by cost constraints or varying levels of regulatory pressure within the sector.

### 4.3.4 Return on Equity (ROE), Performing Loans (PL) and Size based on Total Assets

Table 4.3 provides a summary of the Return on Equity, Performing Loans and Size (as per Total Assets):

**Table 4.3: Summary descriptive statistics for DCP's financial metrics**

| | ROE (%) | | PL (%) | Size (Sh.m) |
|---|---|---|---|---|
| Mean | 3.064516% | | 65.021505% | 263.59 |
| Standard Error | 0.818899% | | 0.530064% | 14.13 |
| Median | 4.000000% | | 65.000000% | 238.00 |
| Mode | -3.000000% | | 66.000000% | 438.00 |
| Standard Deviation | 7.897174% | | 5.111748% | 136.23 |
| Sample Variance | 0.623654% | | 0.261300% | 18559.48 |
| Kurtosis | -1.353592153 | | -0.794919932 | -1.31369457 |
| Skewness | -0.135205323 | | 0.077585915 | 0.099756938 |
| Range | 25.000000% | | 20.000000% | 450.00 |
| Minimum | -10.000000% | | 55.000000% | 49.00 |

| | | | | |
|---|---|---|---|---|
| Maximum | 15.000000% | | 75.000000% | 499.00 |

The financial data reveals relatively modest profitability, with an average ROE of about 3.1% and significant variability, including negative returns for some firms, indicating uneven performance across the sector. Performing Loans, with an average of 65%, suggesting moderate asset quality with some exposure to credit risk. Firm size varies widely, as shown by the large standard deviation, indicating the coexistence of both small and relatively large digital lenders. Overall, the sector appears heterogeneous in both financial performance and scale.

### 4.3.5 Number of Credit Risk Management Trainings and Credit Technologies

Figure 4.5 provides the number of Credit Trainings (annual) and Credit Management Technologies by the credit providers.

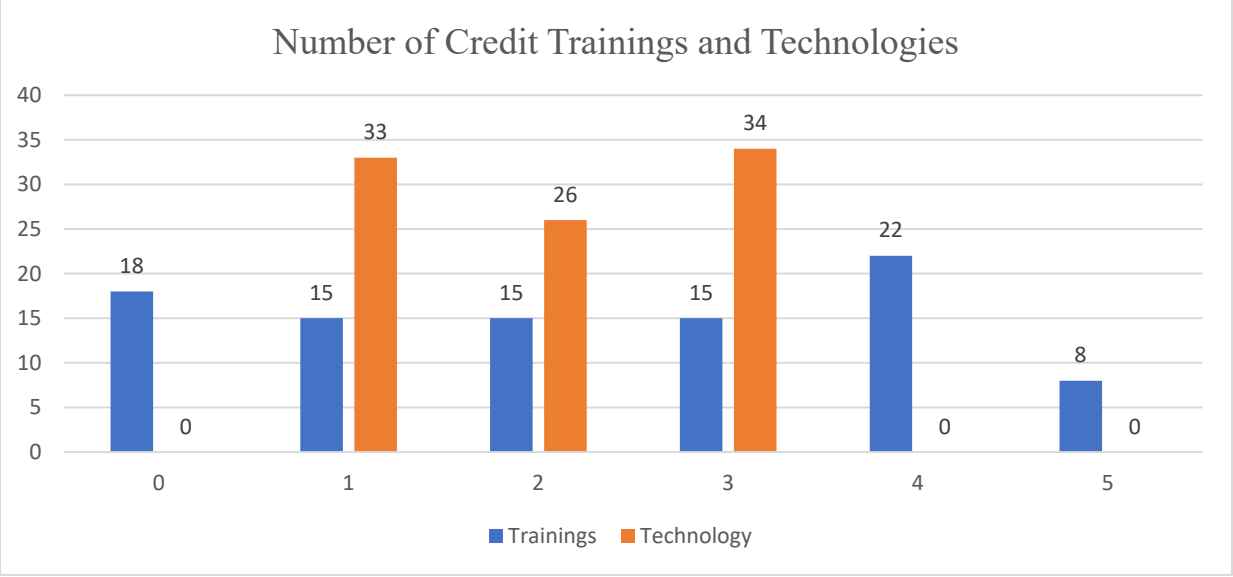



**Figure 4.5: Number of Annual Credit Trainings and Number of Credit Technologies**

The distribution of credit training and technologies suggests differing levels of investment in capacity building and technological adoption. While some firms report multiple annual credit trainings and various technology implementations, others have minimal or none, indicating uneven development in skills and digital infrastructure. The stronger presence of technology adoption

relative to training in some cases may imply a focus on automation over human capital development, which could have implications for long-term risk management effectiveness.

## 4.4 Credit Risk Management Practices

### 4.4.1 Extent of Use of Credit Risk Management Strategies

Question One in Part C requested respondents to indicate the extent to which their organizations use the various risk management strategies.

Table 4.4 summarizes the responses for each strategy.

**Table 4.4: Extent of Use of Credit Risk Management Strategies**

| | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
|---|---|---|---|---|
| 1. Not at all | 20 | 0 | 31 | 0 |
| 2. To a small extent | 14 | 0 | 27 | 9 |
| 3. Moderate extent | 25 | 9 | 13 | 10 |
| 4. Great extent | 22 | 32 | 15 | 37 |
| 5. Very Great extent | 12 | 52 | 7 | 37 |
| Total | 93 | 93 | 93 | 93 |

On other types of credit risk management strategies, only five responses were received. First, establishing strong data governance that includes data validation protocols, standardization, and secure data storage collectively improves the reliability of risk models and reduces model risk arising from poor data inputs. Secondly, deploying explainable AI techniques enables lenders to interpret and justify credit decisions to regulators and customers. Thirdly, regular back-testing, recalibration, and stress testing of credit risk models ensure that they remain predictive under changing economic and borrower behavior conditions. Fourthly, incorporating detailed affordability assessments using verified income streams and spending patterns, which reduces default risk and aligns lending practices with responsible finance principles and regulatory expectations. Finally, applying differentiated pricing based on borrower risk profiles so that higher-risk customers are appropriately priced, compensating for expected losses.

Figure 4.6 provides a summary of responses on the use of credit management strategies.

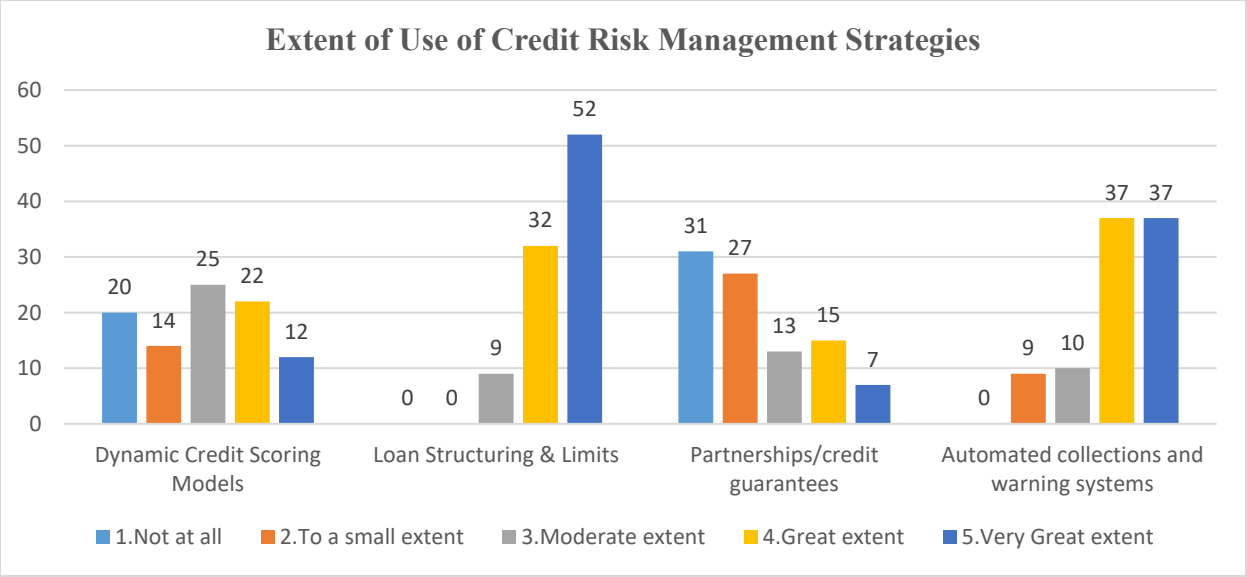



**Figure 4.6: Use of Credit Risk Management Strategies**

Table 4.5 provides a summary of the descriptive statistics

**Table 4.5: Summary Descriptive Statistics on Use of Credit Risk Management Strategies**

| | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
|---|---|---|---|---|
| Mean | 2.913978495 | 4.462365591 | 2.35483871 | 4.096774194 |
| Standard Error | 0.138157171 | 0.069323755 | 0.134721468 | 0.097974479 |
| Median | 3 | 5 | 2 | 4 |
| Mode | 3 | 5 | 1 | 5 |
| Std. Deviation | 1.332339508 | 0.668534084 | 1.299206792 | 0.944831664 |
| Sample Variance | 1.775128565 | 0.446937821 | 1.687938289 | 0.892706872 |
| Kurtosis | -1.126844277 | -0.372451867 | -0.821144187 | 0.00148336 |
| Skewness | -0.064797218 | -0.863551932 | 0.615635228 | -0.907794083 |
| Range | 4 | 2 | 4 | 3 |
| Minimum | 1 | 3 | 1 | 2 |
| Maximum | 5 | 5 | 5 | 5 |

The dataset presents responses from 93 participants on the extent to which four credit risk management practices are used: dynamic credit scoring models, loan structuring and limits, partnerships/credit guarantees, and automated collections and warning systems. Overall, there is clear variation in adoption levels across the four practices. Loan structuring and limits, along with

automated collections, show the highest levels of utilization, while dynamic credit scoring and partnerships/credit guarantees exhibit comparatively lower and more moderate adoption levels.

### 4.4.2 Extent of Use of Dynamic Credit Scoring Models

Question Two in Part C requested that respondents indicate the extent to which they use the various dynamic credit scoring models.

Table 4.6 provides a summary of the responses.

**Table 4.6: Extent of Use of Dynamic Credit Scoring Models**

| | Updating credit scores in real-time based on borrower repayment behavior | Integrating alternative data (e.g., mobile money transactions, utility payments) into credit scoring | Using AI/ML algorithms to adjust scoring criteria in response to market changes | Periodically recalibrating scoring models based on portfolio performance data | Segmenting borrowers dynamically for risk-based loan offers and limits |
|---|---|---|---|---|---|
| 1. Not Used | 18 | 44 | 41 | 19 | 36 |
| 2. Partially Used | 0 | 17 | 15 | 35 | 22 |
| 3. Mostly Used | 15 | 15 | 23 | 12 | 10 |
| 4. Fully Used | 60 | 17 | 14 | 27 | 25 |
| Total | 93 | 93 | 93 | 93 | 93 |

Figure 4.7 provides a summary of the use of various dynamic credit scoring models.

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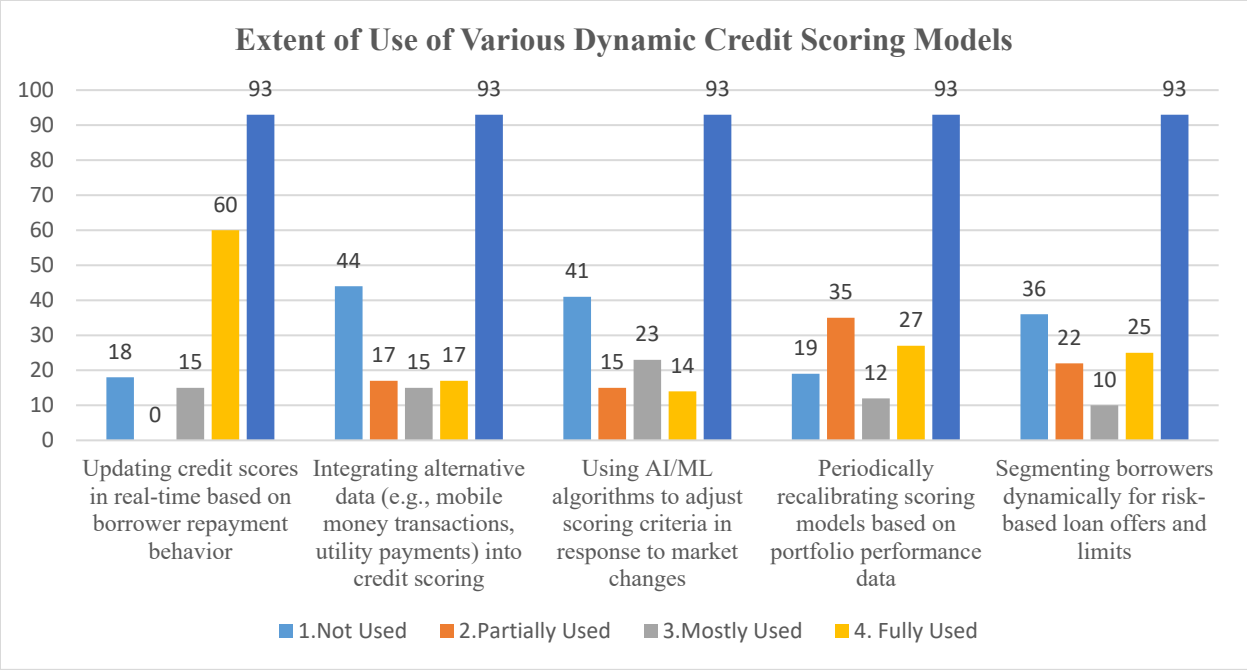



**Figure 4.7: Extent of Use of Various Dynamic Credit Scoring Models**

Table 4.7 provides descriptive statistics on the use of various dynamic credit scoring models.

**Table 4.7: Summary Descriptive Statistics on use of various dynamic credit scoring models**

| | Updating credit scores in real-time based on borrower repayment behavior | Integrating alternative data (e.g., mobile money transactions, utility payments) into credit scoring | Using AI/ML algorithms to adjust scoring criteria in response to market changes | Periodically recalibrating scoring models based on portfolio performance data | Segmenting borrowers dynamically for risk-based loan offers and limits |
|---|---|---|---|---|---|
| Mean | 3.258064516 | 2.053763441 | 2.107526882 | 2.505376344 | 2.258064516 |
| Standard Error | 0.121259583 | 0.121704421 | 0.117896443 | 0.116059318 | 0.127828655 |
| Median | 4 | 2 | 2 | 2 | 2 |
| Mode | 4 | 1 | 1 | 2 | 1 |
| Std Deviation | 1.169385065 | 1.173674936 | 1.136952119 | 1.11923553 | 1.232734904 |
| Sample Variance | 1.367461431 | 1.377512856 | 1.292660122 | 1.252688172 | 1.519635344 |
| Kurtosis | -0.083616302 | -1.203770344 | -1.32385444 | -1.360562491 | -1.475118104 |
| Skewness | -1.271231897 | 0.594637633 | 0.419651604 | 0.17641461 | 0.380486165 |
| Range | 3 | 3 | 3 | 3 | 3 |
| Minimum | 1 | 1 | 1 | 1 | 1 |
| Maximum | 4 | 4 | 4 | 4 | 4 |

The data indicates that the adoption of dynamic credit scoring practices among digital credit providers is uneven, with strong implementation in some areas and limited uptake in others. Notably, updating credit scores in real-time based on borrower repayment behavior shows the highest level of adoption, with the majority of respondents indicating it is "fully used" and a high mean score (≈3.26). In contrast, more advanced and data-intensive approaches, such as integrating alternative data and using AI/ML algorithms, show relatively low adoption levels, with many respondents indicating these are "not used" and mean scores close to 2.

From a distributional perspective, the strong negative skewness for real-time score updating indicates concentration at high usage levels, whereas the positive skewness for other variables reflects clustering at lower usage levels.

### 4.4.3 Extent of Use of Loan Structuring & Limits Practices

Question Three of Part C asked the respondents the extent to which the organization uses the Loan Structuring & Limits practices.

Table 4.8 provides a summary of the responses.

**Table 4.8: Extent of Loan Structuring & Limits**

| | Setting low initial credit limits for new borrowers and increasing them based on repayment history | Offering shorter loan tenures for first-time borrowers to minimize exposure | Differentiating loan limits by customer risk profile | Structuring repayment schedules to match borrowers' income cycles | Applying caps on total exposure to a single borrower or sector |
|---|---|---|---|---|---|
| 1. Not Used | 1 | 27 | 0 | 0 | 0 |
| 2. Partially Used | 20 | 56 | 24 | 24 | 29 |
| 3. Mostly Used | 19 | 10 | 17 | 49 | 42 |
| 4. Fully Used | 53 | 0 | 52 | 20 | 22 |
| Total | 93 | 93 | 93 | 93 | 93 |

Figure 4.8 provides a summary of the extent of loan structuring and limits.

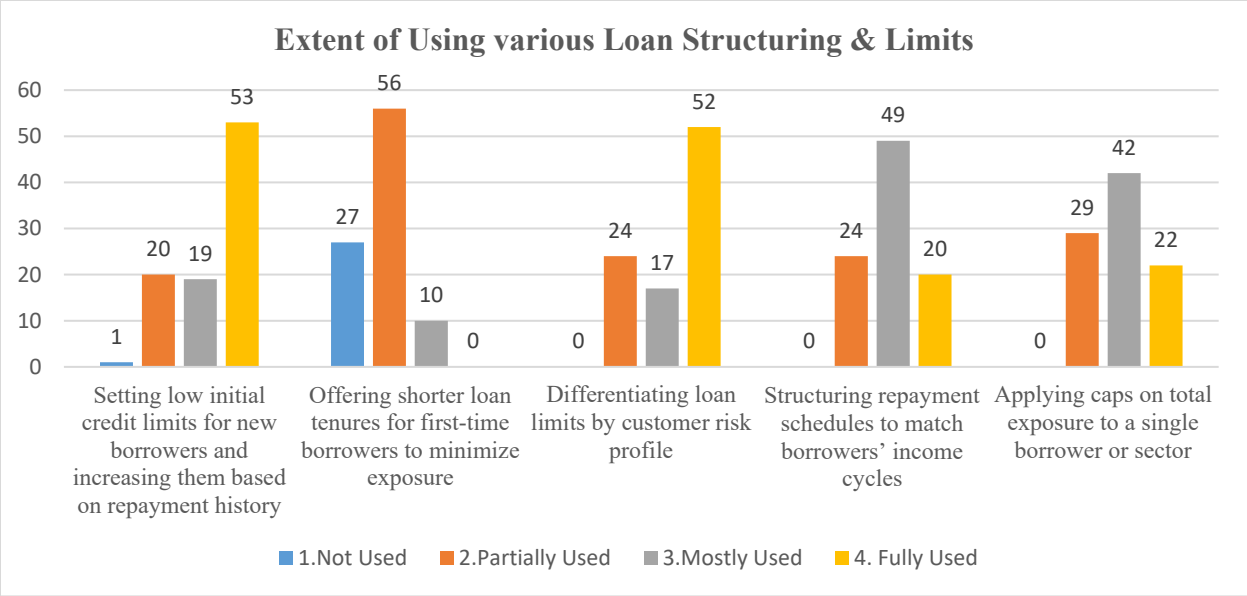



**Figure 4.8: Extent of Use of Various Loan Structuring and Limits**

Table 4.9 provides a summary of the descriptive statistics on the extent of use of various loan structuring limits and limits.

**Table 4.9: Summary Descriptive Statistics on Use of Various Loan Structuring and Limits**

| | Setting low initial credit limits for new borrowers and increasing them based on repayment history | Offering shorter loan tenures for first-time borrowers to minimize exposure | Differentiating loan limits by customer risk profile | Structuring repayment schedules to match borrowers' income cycles | Applying caps on total exposure to a single borrower or sector |
|---|---|---|---|---|---|
| Mean | 3.333333333 | 1.817204301 | 3.301075269 | 2.956989247 | 2.924731183 |
| Standard Error | 0.08827119 | 0.062938479 | 0.088867145 | 0.071571517 | 0.076805917 |
| Median | 4 | 2 | 4 | 3 | 3 |
| Mode | 4 | 2 | 4 | 3 | 3 |
| Std. Deviation | 0.851256531 | 0.606956709 | 0.857003707 | 0.690210719 | 0.740689443 |
| Variance | 0.724637681 | 0.368396447 | 0.734455353 | 0.476390837 | 0.548620851 |
| Kurtosis | -0.812289231 | -0.392399244 | -1.351263477 | -0.86123799 | -1.149210441 |
| Skewness | -0.812373752 | 0.10702227 | -0.627735785 | 0.056169637 | 0.12128761 |
| Range | 3 | 2 | 2 | 2 | 2 |
| Minimum | 1 | 1 | 2 | 2 | 2 |
| Maximum | 4 | 3 | 4 | 4 | 4 |

The data indicates that loan structuring and limits are widely utilized among digital credit providers, though the extent of application varies by specific practice. Setting low initial credit

limits and differentiating loan limits by customer risk profile show the highest levels of adoption, with most respondents indicating these practices are "fully used" and mean scores above 3.3. Moderate adoption is observed in practices such as structuring repayment schedules to match borrowers' income cycles and applying caps on total exposure. These practices have mean values close to 3, indicating they are generally "mostly used," reflecting a growing emphasis on cash flow-aligned lending and portfolio risk control. However, the distribution of responses suggests that implementation is not yet uniform across all institutions, pointing to varying levels of sophistication in credit structuring approaches. In contrast, offering shorter loan tenures for first-time borrowers is the least adopted practice, with a low mean (≈1.82) and a concentration of responses in the "partially used" and "not used" categories. This implies that many providers may prioritize rapid credit access and customer acquisition over conservative tenure restrictions. Overall, the findings suggest that while core risk-based structuring practices are well embedded, some more conservative credit control measures are less emphasized, highlighting a trade-off between growth objectives and risk mitigation.

### 4.4.4 Extent of Use of Partnerships/Credit Guarantees

Question Four of Part C asked the respondents the extent to which the organization uses Partnerships and Credit guarantee practices.

Table 4.10 provides a summary of the responses.

**Table 4.10: Use of Partnerships/Credit guarantees**

| | Partnering with credit bureaus to access and share borrower credit history | Collaborating with fintech firms or banks to share risk and customer data | Using government or development agency credit guarantee schemes | Partnering with insurance providers to cover potential loan defaults | Co-lending or syndicated lending with other institutions to reduce exposure |
|---|---|---|---|---|---|
| 1. Not Used | 31 | 40 | 74 | 44 | 74 |
| 2. Partially Used | 0 | 37 | 19 | 13 | 19 |
| 3. Mostly Used | 12 | 16 | 0 | 19 | 0 |
| 4. Fully Used | 50 | 0 | 0 | 17 | 0 |
| Total | 93 | 93 | 93 | 93 | 93 |

Figure 4.9 provides a summary of the responses:

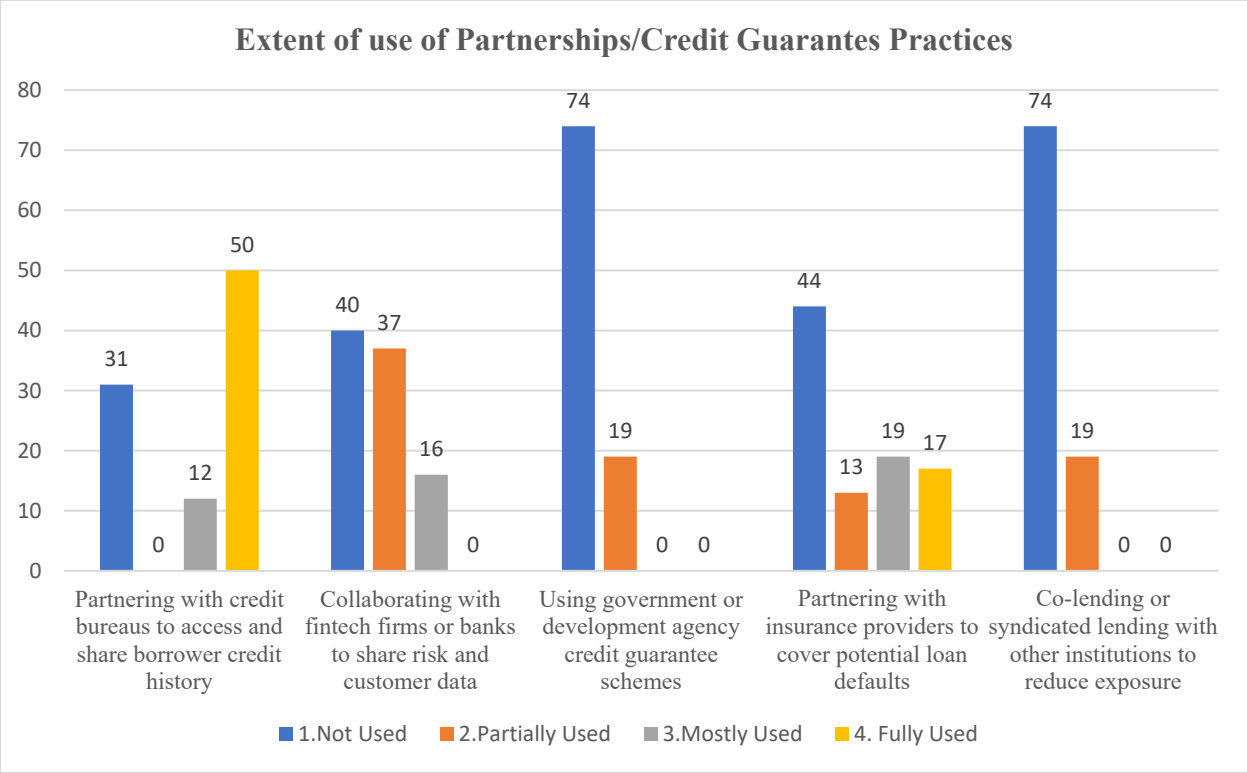



**Figure 4.9: Extent of use of Partnerships/Credit Guarantees**

Table 4.11 provides a summary of the descriptive statistics.

**Table 4.11: Summary descriptive statistics on the extent of use of Partnerships/Credit Guarantees**

| | Partnering with credit bureaus to access and share borrower credit history | Collaborating with fintech firms or banks to share risk and customer data | Using government or development agency credit guarantee schemes | Partnering with insurance providers to cover potential loan defaults | Co-lending or syndicated lending with other institutions to reduce exposure |
|---|---|---|---|---|---|
| Mean | 2.870967742 | 1.741935484 | 1.204301075 | 2.096774194 | 1.204301075 |
| Standard Error | 0.141970543 | 0.076296991 | 0.042035459 | 0.123325167 | 0.042035459 |
| Median | 4 | 2 | 1 | 2 | 1 |
| Mode | 4 | 1 | 1 | 1 | 1 |
| Std Deviation | 1.369114332 | 0.73578154 | 0.40537529 | 1.18930484 | 0.40537529 |
| Variance | 1.874474053 | 0.541374474 | 0.164329126 | 1.414446003 | 0.164329126 |
| Kurtosis | -1.577766756 | -1.02743329 | 0.227364669 | -1.364273383 | 0.227364669 |
| Skewness | -0.567223466 | 0.450608315 | 1.490953246 | 0.482955651 | 1.490953246 |
| Range | 3 | 2 | 1 | 3 | 1 |
| Minimum | 1 | 1 | 1 | 1 | 1 |
| Maximum | 4 | 3 | 2 | 4 | 2 |

The data indicates that the use of partnerships and credit guarantee practices among digital credit providers is generally low and unevenly distributed. The only relatively well-adopted practice is partnering with credit bureaus to access and share borrower credit history, which records the highest mean (≈2.87) and many "fully used" responses. In contrast, other collaborative practices, such as working with fintech firms or banks, partnering with insurance providers, and especially using government credit guarantee schemes, show limited adoption. These variables have low mean scores (mostly below 2.1), with a high concentration of responses in the "not used" or "partially used" categories.

Particularly notable is the very low uptake of government/development credit guarantees and co-lending or syndicated lending, both with mean scores around 1.2 and strong positive skewness, indicating that most firms do not utilize these mechanisms at all. Overall, the findings suggest that digital credit providers rely more on internal risk management systems than on external risk-sharing arrangements, highlighting a significant gap in leveraging partnerships to diversify and mitigate credit risk exposure.

### 4.4.4 Extent of Use of Automated Collections and Warning Systems

Question Five of Part C asked the respondents the extent to which the organization uses Automated Collections and Warning Systems.

Table 4.12 provides a summary of the responses.

**Table 4.12: Extent of Use of Automated Collections and Warning Systems**

| | Sending automated SMS or app notifications to remind borrowers of upcoming repayments | Using predictive analytics to detect early signs of repayment difficulties | Automating follow-up actions for overdue accounts (e.g., calls, emails) | Monitoring borrower transaction patterns to flag potential defaults | Integrating repayment reminders with borrowers' preferred payment channels (e.g., mobile money push prompts) |
|---|---|---|---|---|---|
| 1. Not Used | 0 | 23 | 38 | 17 | 25 |
| 2. Partially Used | 0 | 21 | 19 | 24 | 21 |
| 3. Mostly Used | 34 | 27 | 21 | 24 | 27 |
| 4. Fully Used | 59 | 22 | 15 | 28 | 20 |
| Total | 93 | 93 | 93 | 93 | 93 |

Figure 4.10 also provides a summary of the results:

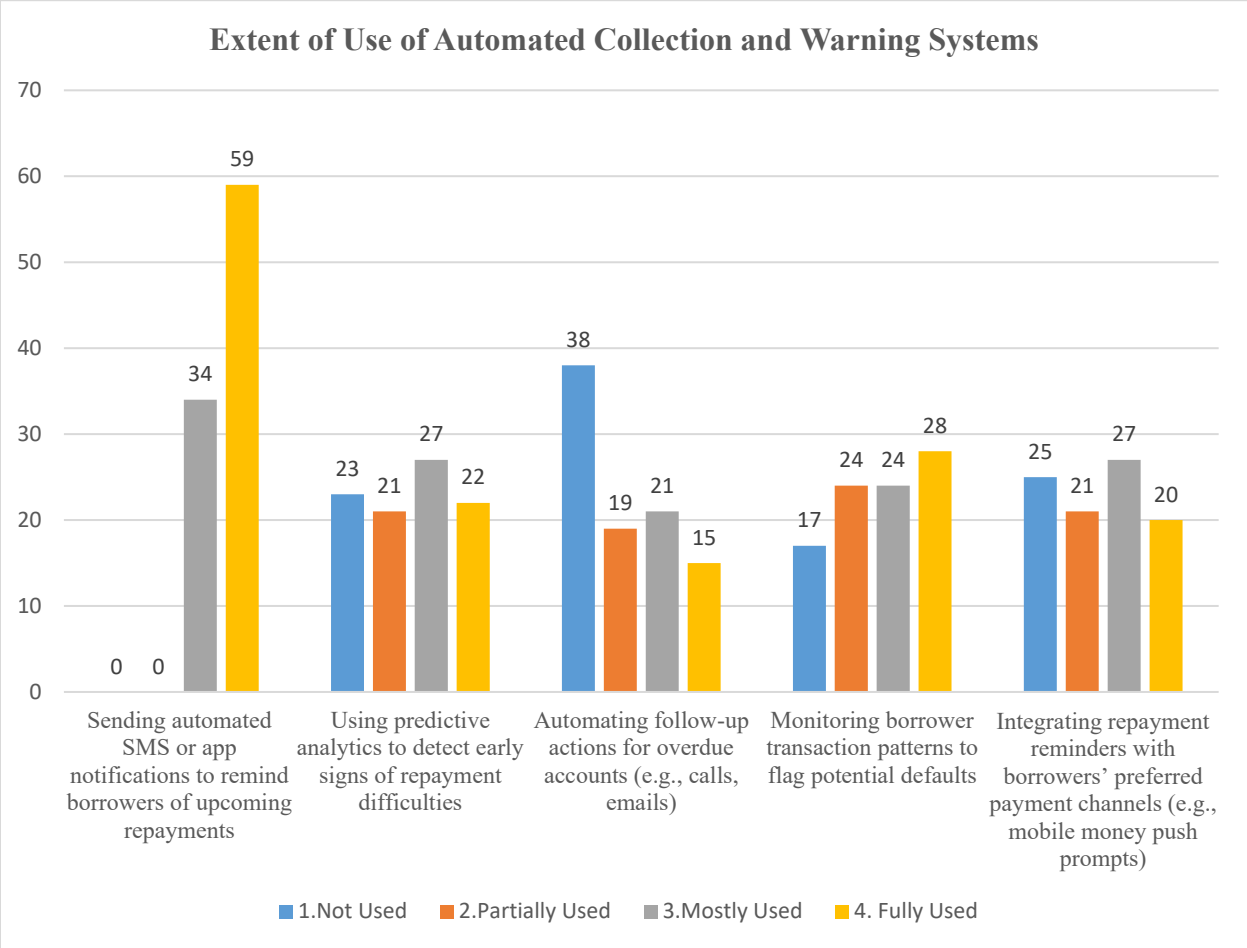



**Figure 4.10: Extent of Use of Automated Collection and Warning Systems**

Table 4.13 provides descriptive statistics of the extent of use of Automated Collection and Warning Systems

**Table 4.13: Summary Descriptive Statistics on use of Automated Collection Warning Systems**

| | Sending automated SMS or app notifications to remind borrowers of upcoming repayments | Using predictive analytics to detect early signs of repayment difficulties | Automating follow-up actions for overdue accounts (e.g., calls, emails) | Monitoring borrower transaction patterns to flag potential defaults | Integrating repayment reminders with borrowers' preferred payment channels (e.g., mobile money push prompts) |
|---|---|---|---|---|---|
| Mean | 3.634408602 | 2.516129032 | 2.139784946 | 2.677419355 | 2.451612903 |
| Standard Error | 0.050209813 | 0.115036941 | 0.117029821 | 0.113552531 | 0.114938576 |

| | | | | | |
|---|---|---|---|---|---|
| Median | 4 | 3 | 2 | 3 | 3 |
| Mode | 4 | 3 | 1 | 4 | 3 |
| Std Deviation | 0.484205899 | 1.10937608 | 1.128594719 | 1.09506095 | 1.10842749 |
| Variance | 0.234455353 | 1.230715288 | 1.27372604 | 1.199158485 | 1.228611501 |
| Kurtosis | -1.71545583 | -1.329711312 | -1.274963325 | -1.28031647 | -1.338074408 |
| Skewness | -0.567372837 | -0.065935589 | 0.41423181 | -0.187074792 | 0.002393633 |
| Range | 1 | 3 | 3 | 3 | 3 |
| Minimum | 3 | 1 | 1 | 1 | 1 |
| Maximum | 4 | 4 | 4 | 4 | 4 |

The data shows that automated collections and warning systems are widely adopted among digital credit providers, particularly for basic and customer-facing functions. Sending automated SMS or app notifications for repayment reminders is the most extensively used practice, with a high mean score (≈3.63) and a strong concentration of "fully used" responses. Moderate adoption is observed in more analytical and monitoring-based practices, such as using predictive analytics to detect early repayment difficulties and monitoring borrower transaction patterns. These practices have mean scores ranging between approximately 2.5 and 2.7, suggesting they are "mostly used" but not yet fully embedded across all institutions. In contrast, automating follow-up actions for overdue accounts and integrating repayment reminders with preferred payment channels show comparatively lower adoption levels, with mean scores closer to 2.1–2.5 and more dispersed responses.

### 4.4.5 The extent to which the Credit Management Strategies are Effective

Question Six of Part C asked the respondents the extent to which the various credit management strategies are effective

Table 4.14 provides a summary of the responses.

**Table 4.14: Extent to which the Credit Management Strategies are Effective**

| | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
|---|---|---|---|---|
| 1. Not effective | 17 | 19 | 16 | 21 |
| 2. Effective to a small extent | 15 | 19 | 20 | 17 |
| 3. Effective moderately | 24 | 22 | 25 | 20 |
| 4. Effective to a great extent | 17 | 10 | 20 | 14 |
| 5. Effective to a very great extent | 20 | 23 | 12 | 21 |

| | | | | |
|---|---|---|---|---|
| Total | 93 | 93 | 93 | 93 |

Figure 4.11 provides a summary of the responses

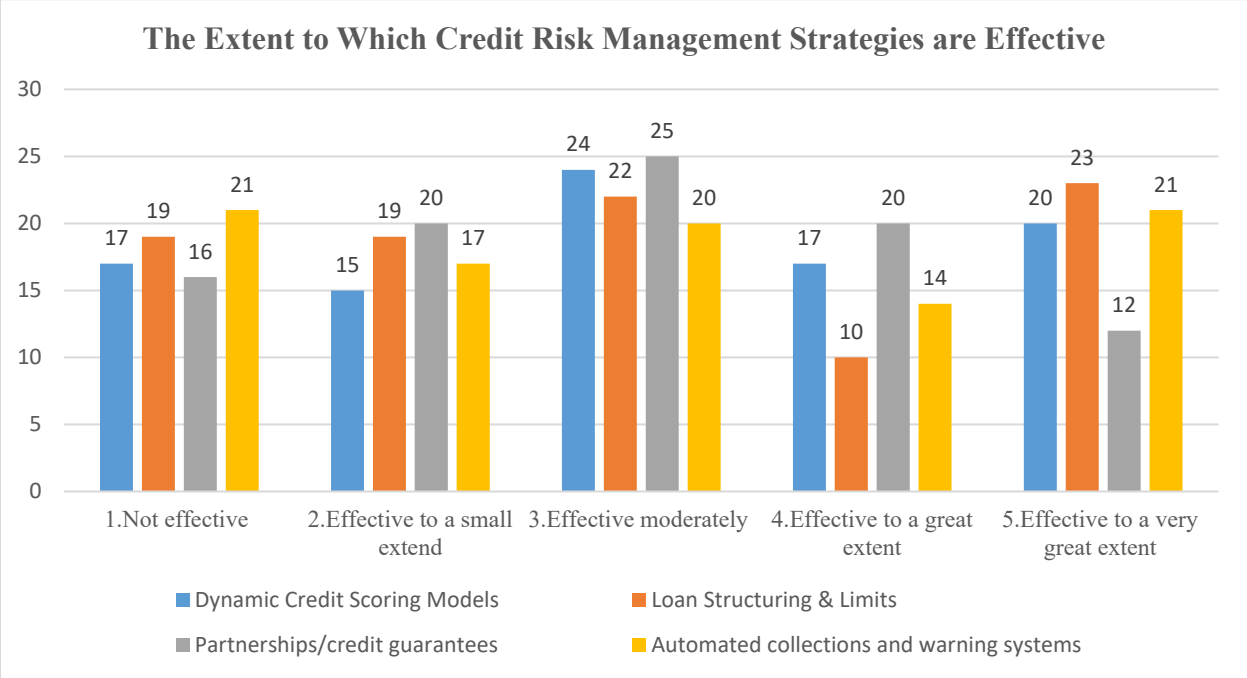



**Figure 4.11: Extent to which Credit Risk Management Strategies are Effective**

Table 4.15 provides a summary of the descriptive statistics on the effectiveness of the credit risk management strategies.

**Table 4.15: Summary Descriptive Statistics on Effectiveness of Credit Risk Management Strategies**

| | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
|---|---|---|---|---|
| Mean | 3.086021505 | 2.989247312 | 2.913978495 | 2.967741935 |
| Standard Error | 0.144766835 | 0.151735036 | 0.132984508 | 0.152470395 |
| Median | 3 | 3 | 3 | 3 |
| Mode | 3 | 5 | 3 | 1 |
| Standard Deviation | 1.396080803 | 1.463279697 | 1.282456152 | 1.47037124 |
| Sample Variance | 1.949041608 | 2.141187471 | 1.644693782 | 2.161991585 |
| Kurtosis | -1.1975103 | -1.323541187 | -1.025618765 | -1.353280195 |
| Skewness | -0.083009572 | 0.104075371 | 0.037431532 | 0.056790378 |
| Range | 4 | 4 | 4 | 4 |

| | | | | |
|---|---|---|---|---|
| Minimum | 1 | 1 | 1 | 1 |
| Maximum | 5 | 5 | 5 | 5 |

The data indicates that all four credit risk management strategies, dynamic credit scoring models, loan structuring and limits, partnerships/credit guarantees, and automated collections, are perceived to be moderately effective overall. This is reflected in mean scores clustered around 3 and median values of 3 across all variables, suggesting that respondents generally rate these strategies as "moderately effective." The relatively even distribution of responses across effectiveness levels further implies that no single strategy overwhelmingly outperforms the others in perceived impact.

Dynamic credit scoring models show a slightly higher mean (≈3.09), indicating a marginally stronger perception of effectiveness compared to the other strategies. Loan structuring and limits, as well as automated collections systems, also demonstrate comparable effectiveness, though responses are more dispersed, as reflected in higher standard deviations. Partnerships and credit guarantees, while still moderately rated, do not stand out for effectiveness, aligning with earlier findings that show their relatively low adoption.

From a distributional perspective, the near-zero skewness across all variables indicates a balanced spread of opinions, while the negative kurtosis suggests flatter distributions with fewer extreme responses. Notably, a significant number of respondents still rate these strategies as either "not effective" or only effective to a small extent, highlighting gaps in implementation quality or contextual challenges.

## 4.5 Organizational Factors associated with Credit Risk Management Strategies

### 4.5.1 Correlation Analysis

Table 4.16 provides a key for the variables used in establishing the pairwise correlation.

**Table 4.16: Key for the variables used in the correlation analysis**

| | |
|---|---|
| Years | Yrs |
| Board Size | BoardS |
| Credit Committee | CC |
| ROE | ROE |

| | |
|---|---|
| Performing Loans | PL |
| Size – Assets | Assets |
| Auditor | Auditor |
| CM Trainings | CMTR |
| CM Technology | CMTECH |
| Dynamic Credit Scoring Models | DCSM |
| Loan Structuring & Limits | LSL |
| Partnerships/credit guarantees | PCG |
| Automated collections and warning systems | ACS |

Table 4.17 provides the pairwise corrections

**Table 4.17 Pairwise Correlations**

| | Yrs | BoardS | CC | ROE | PL | Assets | Auditor | CMTR | CMTECH | DCSM | LSL | PCG | ACS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yrs | 1 | | | | | | | | | | | | |
| BoardS | -0.15 | 1 | | | | | | | | | | | |
| | 0.159 | | | | | | | | | | | | |
| CC | -0.13 | 0.81* | 1 | | | | | | | | | | |
| | 0.212 | 0 | | | | | | | | | | | |
| ROE | -0.05 | 0.146 | -0.010 | 1 | | | | | | | | | |
| | 0.604 | 0.160 | 0.9199 | | | | | | | | | | |
| PL | -0.05 | -0.02 | -0.075 | 0.162 | 1 | | | | | | | | |
| | 0.570 | 0.782 | 0.473 | 0.120 | | | | | | | | | |
| Assets | -0.2* | -0.12 | -0.102 | -0.04 | -0.037 | 1 | | | | | | | |
| | 0.048 | 0.219 | 0.327 | 0.674 | 0.723 | | | | | | | | |
| Auditor | -0.10 | 0.014 | -0.021 | 0.023 | -0.032 | 0.78* | 1 | | | | | | |
| | 0.329 | 0.888 | 0.844 | 0.823 | 0.76 | 0 | | | | | | | |
| CMTR | 0.061 | -0.02 | 0.0546 | 0.067 | 0.0622 | 0.064 | -0.09 | 1 | | | | | |
| | 0.558 | 0.853 | 0.603 | 0.520 | 0.5537 | 0.540 | 0.415 | | | | | | |
| CMTECH | 0.082 | 0.061 | 0.0098 | -0.10 | -0.047 | 0.012 | 0.026 | -0.164 | 1 | | | | |
| | 0.430 | 0.560 | 0.9254 | 0.316 | 0.6519 | 0.909 | 0.800 | 0.1149 | | | | | |
| DCSM | -0.06 | 0.050 | 0.0668 | 0.070 | -0.046 | 0.124 | 0.23* | -0.090 | -0.2 | 1 | | | |
| | 0.562 | 0.628 | 0.5246 | 0.500 | 0.661 | 0.233 | 0.030 | 0.3903 | 0.0547 | | | | |
| LSL | 0.107 | 0.035 | -0.061 | 0.091 | 0.1275 | 0.044 | -0.02 | 0.1103 | 0.0293 | 0.131 | 1 | | |
| | 0.307 | 0.739 | 0.5636 | 0.385 | 0.2234 | 0.675 | 0.983 | 0.2926 | 0.7804 | 0.209 | | | |
| PCG | 0.144 | 0.041 | 0.0587 | 0.055 | 0.0037 | -0.13 | -0.02 | -0.088 | 0.0259 | -0.01 | -0.27* | 1 | |
| | 0.167 | 0.695 | 0.576 | 0.601 | 0.9716 | 0.210 | 0.890 | 0.4021 | 0.8051 | 0.992 | 0.0096 | | |
| ACS | -0.06 | 0.039 | -0.038 | 0.060 | 0.0018 | 0.021 | -0.04 | 0.041 | 0.0931 | -0.13 | 0.1005 | -0.17 | 1 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.574 | 0.705 | 0.717 | 0.565 | 0.9862 | 0.844 | 0.717 | 0.6956 | 0.3749 | 0.238 | 0.3353 | 0.1015 | |

The pairwise correlation results indicate that most relationships between variables are weak and statistically insignificant, suggesting a low degree of linear association across the dataset. This implies that the various organizational, financial, and credit risk management variables largely operate independently rather than being strongly interrelated. In practical terms, no single factor appears to drive or predict another across digital credit providers consistently (Donaldson, 2001)

However, a few statistically significant relationships stand out. There is a strong positive correlation between board size and the presence of a credit committee (≈0.81), indicating that institutions with larger boards are more likely to have formal credit governance structures. Additionally, firm size (assets) is strongly positively correlated with the type of auditor (≈0.78), suggesting that larger firms are more likely to engage top-tier auditors, reflecting stronger governance and compliance requirements (Tricker, 2019).

Among the credit risk practices, a modest positive correlation exists between the use of dynamic credit scoring models and the type of auditor (≈0.23), implying that firms with stronger audit frameworks may also adopt more advanced risk assessment tools. Conversely, there is a weak but significant negative relationship between loan structuring & limits and partnerships/credit guarantees (≈-0.27), suggesting that firms relying more on internal structuring mechanisms may be less inclined to engage in external risk-sharing arrangements (Knechel & Salterio, 2017).

Overall, the findings highlight that while a few governance and structural variables exhibit meaningful relationships, most operational and risk management practices show limited interdependence. This suggests a fragmented approach to credit risk management, where institutions adopt strategies independently rather than as part of a fully integrated framework.

### 4.5.2 Multivariate Analysis

The multivariate analysis was carried out using multinomial logit regression, with four separate analyses being applied for each credit management strategy. Table 4.15 presents the summary of the output of the model.

**Table 4.18: Summary Multivariate Analysis**

| | | Dependent Variable | | | |
|---|---|---|---|---|---|
| | | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
| No. of observations | | 92 | 92 | 92 | 92 |
| LR chi2(36) | | 51.99 | 19.22 | 31.15 | 19.53 |
| Prob > chi2 | | 0.0412 | 0.3786 | 0.6985 | 0.8499 |
| Pseudo R2 | | 0.1794 | 0.1133 | 0.1135 | 0.0894 |
| Log likelihood | | -188.92182 | -75.194965 | -121.67986 | -99.48205 |
| Constant | Coef. | 4.301229 | -0.3825572 | -12.19022 | -2.057902 |
| | Std Err. | 4.838262 | 6.093873 | 4.701456 | 3.610973 |
| | z | 0.89 | -0.06 | -2.59 | -0.57 |
| | P>z | 0.374 | 0.95 | 0.01 | 0.569 |
| Independent Variables | | Dynamic Credit Scoring Models | Loan Structuring & Limits | Partnerships/credit guarantees | Automated collections and warning systems |
| Years | Coef. | 0.158931 | -0.1184861 | -0.0445804 | 0.0010224 |
| | Std Err. | 0.1191641 | 0.1434439 | 0.1091396 | 0.088721 |
| | z | 1.33 | -0.83 | -0.41 | 0.01 |
| | P>z | 0.09*** | 0.409 | 0.683 | 0.991 |
| Board Size | Coef. | 0.0968084 | -0.3569638 | 0.3473143 | 0.3256503 |
| | Std Err. | 0.3553004 | 0.4302644 | 0.3169835 | 0.2744912 |
| | z | 0.27 | -0.83 | 1.1 | 1.19 |
| | P>z | 0.785 | 0.407 | 0.273 | 0.235 |
| Credit Committee | Coef. | 0.05052 | 1.231987 | -0.7569563 | -0.8191155 |
| | Std Err. | 1.120607 | 1.346406 | 1.018485 | 0.8919358 |
| | z | 0.05 | 0.92 | -0.74 | -0.92 |
| | P>z | 0.964 | 0.36 | 0.457 | 0.358 |
| ROE % | Coef. | -4.171932 | -1.013873 | -3.781539 | -2.5267 |
| | Std Err. | 4.409836 | 5.306594 | 3.796646 | 3.230488 |
| | z | -0.95 | -0.19 | -1 | -0.78 |

| | | | | | |
|---|---|---|---|---|---|
| | P>z | 0.344 | 0.848 | 0.319 | 0.084*** |
| Performing Loans % | Coef. | -7.438769 | 1.257512 | 16.16236 | 0.834714 |
| | Std Err. | 6.782251 | 7.632228 | 6.239872 | 4.776832 |
| | z | -1.1 | 0.16 | 2.59 | 0.17 |
| | P>z | 0.273 | 0.869 | 0.45 | 0.861 |
| Size – Assets | Coef. | -0.0021655 | 0.0007408 | 0.0006295 | -0.0002721 |
| | Std Err. | 0.0044901 | 0.0059309 | 0.0040052 | 0.0032025 |
| | z | -0.48 | 0.12 | 0.16 | -0.08 |
| | P>z | 0.03** | 0.901 | 0.875 | 0.932 |
| Auditor | Coef. | 0.9524845 | -0.3811138 | -0.0977553 | 0.1934173 |
| | Std Err. | 1.247154 | 1.573685 | 1.079636 | 0.8832284 |
| | z | 0.76 | -0.24 | -0.09 | 0.22 |
| | P>z | 0.445 | 0.809 | 0.928 | 0.827 |
| CM Trainings | Coef. | 0.0802492 | -0.450623 | 0.1145866 | 0.1541378 |
| | Std Err. | 0.2075058 | 0.2658068 | 0.1857298 | 0.1541806 |
| | z | 0.39 | -1.7 | 0.62 | 1 |
| | P>z | 0.699 | 0.09*** | 0.537 | 0.317 |
| CM Technology | Coef. | -0.54468 | 0.2058598 | 0.0401886 | 0.0291247 |
| | Std Err. | 0.3865122 | 0.4789383 | 0.3500111 | 0.2886153 |
| | z | -1.41 | 0.43 | 0.11 | 0.1 |
| | P>z | 0.159 | 0.667 | 0.909 | 0.92 |

Key *-1%, **-5%, ***-10% significance level.

The results show generally weak associations between dynamic credit scoring models and most independent variables, with coefficients indicating mixed positive and negative relationships. However, years of operation (positive, weak significance at 10%) and firm size (assets) (negative, significant at 5%) emerge as relevant predictors. In terms of model diagnostics, the model is statistically significant overall (Prob > chi2 = 0.0412), with a moderate explanatory power (Pseudo $R^2 \approx 0.18$), indicating a reasonably good fit relative to the other models.

The associations between loan structuring practices and the independent variables are generally weak and statistically insignificant. The only marginally significant variable is credit management training (negative at 10%). Model diagnostics show that the model is not statistically significant (Prob > chi2 = 0.3786) and has low explanatory power (Pseudo $R^2 \approx 0.11$), indicating a poor overall fit.

The model reveals weak and largely insignificant relationships between partnerships/credit guarantees and independent variables, with no strong predictors emerging. Although performing loans show a positive coefficient, it is not statistically significant, indicating no reliable influence. Overall, none of the independent variables significantly explains the variation in this dependent variable. Model diagnostics confirm this, with a non-significant model (Prob > chi2 = 0.6985) and low explanatory power (Pseudo $R^2 \approx 0.11$), suggesting that other unobserved factors may drive partnership adoption.

The associations between automated systems and independent variables are also weak, with most variables showing no statistical significance. The only marginal influence is ROE (negative at 10%) though the relationship is weak. Model diagnostics indicate that the model is not statistically significant (Prob > chi2 = 0.8499) and has the lowest explanatory power (Pseudo $R^2 \approx 0.09$), implying that the included variables do not adequately explain the adoption of automated systems.

## 4.6 Management Perspectives on Credit Risk Management

### 4.6.1 The Use of Technology and AI in Credit Risk Management

Question Seven of Part C asked the respondents to comment on the use of technology, such as AI-driven credit scoring or automated collections, that influenced the organization's ability to manage credit risk. Only 19 responses were received from the 93 participants.

Table 4.19 provides a summary of the key areas of responses and the number of responses

**Table 4.19: The use of technology and AI in Credit Risk Management**

| **Key areas of response** | Number |
|---|---|
| AI-driven models use alternative data (e.g., mobile usage, transaction history) to generate credit scores for thin-file customers. | 5 |
| AI/Machine learning algorithms improve credit scoring accuracy by continuously learning from repayment behavior. | 4 |
| Real-time data processing enables instant credit decisions, reducing exposure to high-risk applicants. | 3 |
| AI systems detect early warning signals of default through behavioral and transactional pattern analysis. | 1 |
| Automated risk segmentation allows lenders to differentiate borrowers into granular risk tiers for better pricing. | 1 |
| Predictive analytics enhances the probability of default (PD) estimation, strengthening risk-based lending decisions. | 1 |

| | |
|---|---|
| AI-powered fraud detection tools identify suspicious applications and synthetic identities before loan approval. | 1 |
| Continuous monitoring models enable dynamic credit limit adjustments based on borrower performance. | 1 |
| Natural language processing (NLP) helps analyze customer communication and sentiment to flag potential distress. | 1 |
| Automation of collections strategies uses AI to optimize repayment reminders and recovery actions, improving loan performance. | 1 |

The findings indicate that digital credit providers are increasingly leveraging artificial intelligence and machine learning to enhance credit risk management, particularly with alternative data and adaptive credit scoring models. The most cited application of AI-driven models using non-traditional data such as mobile usage and transaction histories suggests a strong shift toward financial inclusion, especially for thin-file customers who lack formal credit histories.

### 4.6.2 Challenges in implementing Credit Risk Management strategies

Question Eight of Part C requested respondents to highlight the main challenges faced by the organization in implementing credit risk management strategies in the digital lending environment. Nearly 62 responses were received.

Table 4.20 provides a summary of the responses

**Table 4.20: Challenges in Implementing Credit Risk Management Strategies**

| Key Areas of responses | Number |
|---|---|
| Limited availability of high-quality data constrains the accuracy and reliability of AI-driven credit models. | 8 |
| Data privacy and protection regulations (e.g., enforced by the Central Bank of Kenya) restrict the use of certain alternative data sources. | 8 |
| Algorithmic bias and fairness concerns can lead to discriminatory lending outcomes and regulatory scrutiny. | 6 |
| High implementation and infrastructure costs limit the ability of smaller DCPs to deploy advanced AI solutions. | 6 |
| Lack of explainability (“black box” models) makes it difficult to justify credit decisions to regulators and customers. | 6 |
| Cybersecurity risks increase as digital platforms and data volumes expand. | 6 |
| Integration challenges with legacy systems hinder the seamless deployment of AI tools. | 5 |
| Shortage of skilled AI and data science talent constrains model development and validation. | 4 |
| Model risk and overfitting can lead to inaccurate predictions, especially in volatile economic conditions. | 4 |

| | |
|---|---|
| Rapidly changing borrower behavior reduces the stability and predictive power of AI models over time. | 4 |
| Regulatory uncertainty and evolving compliance requirements create ambiguity in AI adoption strategies. | 3 |
| Customer mistrust and low transparency may limit acceptance of AI-driven credit decisions. | 2 |

The most prominent issues, limited availability of high-quality data and stringent data privacy regulations, highlight a fundamental tension between the need for rich data to power AI models and the requirement to protect consumer information. This suggests that data governance remains a critical bottleneck in digital lending. Furthermore, the respondents highlight concerns around algorithmic bias, lack of explainability, and cybersecurity risks. From an operational perspective, challenges such as high implementation costs, integration with legacy systems, and shortages of skilled personnel underscore structural barriers that disproportionately affect smaller digital credit providers. The presence of model risk, rapidly changing borrower behavior, and regulatory uncertainty further complicates the deployment and sustainability of AI models.

### 4.6.3 Changes/innovations to enhance Credit Risk Management for digital Lending

Question Nine of Part C asked the participants to provide their views on the changes or innovations that could further enhance credit risk management for digital credit lending in the future. Here, 41 responses were received.

Table 4.21 provides a summary of the key responses:

**Table 4.21: Changes/Innovations to enhance Credit Risk Management for Digital Lending**

| Key responses | Number |
|---|---|
| Implement robust, explainable credit scoring models to ensure transparency and regulatory compliance in lending decisions. | 8 |
| Strengthen customer affordability assessments using verified income and cash flow data to prevent over-indebtedness. | 6 |
| Align lending practices with guidelines issued by regulators such as the Central Bank of Kenya to ensure full compliance. | 6 |
| Establish clear pricing structures and disclosures to enhance borrower understanding and reduce disputes. | 5 |
| Use responsible data governance frameworks to protect customer data and comply with privacy laws. | 5 |
| Implement early warning systems and proactive monitoring to detect repayment stress and intervene promptly. | 4 |

| | |
|---|---|
| Adopt ethical collection practices supported by automation to maintain customer trust and regulatory adherence. | 4 |
| Regularly conduct model validation and stress testing to ensure credit risk models remain accurate under changing conditions. | 3 |

The most frequently cited recommendation, adoption of explainable AI models as well as strengthening affordability assessments and aligning with regulatory guidelines reflects a shift toward more responsible lending practices aimed at reducing over-indebtedness and improving financial stability.

In addition, the emphasis on data governance, clear pricing structures, and proactive monitoring mechanisms and recommendations, such as ethical collections, model validation, and stress testing, further reinforces the importance of maintaining model robustness and adaptability in dynamic economic environments.

## 4.7 Summary of the Chapter

Chapter Four presented the findings and results of the study. Responses were obtained from 93 participants, playing an important role in credit risk management of the digital credit providers. The study has provided insights into the common digital credit management strategies, as well as the examples under each strategy. This was complemented by descriptive statistics and multivariate analysis on organizational factors influencing the use of the various credit management Strategies. Chapter Five, the last, provides the discussions and conclusions of the study.

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# CHAPTER FIVE: DISCUSSIONS AND CONCLUSION

## 5.1 Introduction

Chapter Five concludes the thesis with discussions, conclusions, limitations, and recommendations for further studies. Chapter One provided the introduction and background, objectives, and justification of the study. The general objective of this study was to establish organizational factors influencing the prioritization of credit management strategies by digital credit providers in Kenya. Chapter Two presented the theories (Resource-Based View-RBV and Prospect Theory -PT) and key empirical studies. Chapter Three explained the methodology of the study; the philosophy (a positivist and, minimally, post-positivism), design (concurrent qualitative and quantitative), population (153 digital credit providers), data collection tool (online administered questionnaire to senior officers of the digital credit providers in charge of credit), data analysis (combining both descriptive and multivariate analysis), as well as quality and ethical issues of the study. Chapter Four presented the findings and results, with only 93 respondents of the 153 digital credit providers.

## 5.2 Discussions

### 5.2.1 Credit risk Management strategies prioritized by digital credit providers in Kenya

According to the findings and results, digital credit providers rank loan structuring & Limits as the most popular credit risk management strategy (with a mean of 4.46), followed by Automated Collections and Warnings Systems (mean of 4.096), then Dynamic Credit Scoring Models (Mean of 2.91) and finally partnerships/Credit guarantees (mean of 2.35). Several possible reasons may explain this outcome. First, operational simplicity and immediate control over risk exposure make loan structuring and limits the most preferred strategy, as these tools (e.g., setting credit caps, repayment terms) are internally controlled, easy to implement, and directly aligned with core lending processes.

Another reason could be due to cost-efficiency and scalability of automation drive the high adoption of automated collections and warning systems, since technologies like SMS reminders and basic analytics deliver quick wins in reducing delinquency without requiring sophisticated infrastructure. Finally, resource, capability, and ecosystem constraints limit the uptake of dynamic

credit scoring models and partnerships/credit guarantees: advanced scoring requires high-quality data, AI expertise, and regulatory clarity, while partnerships depend on external coordination, trust frameworks, and availability of guarantee schemes factors that are often underdeveloped or costly, leading to their comparatively low adoption.

As per the findings and results, in using dynamic credit scoring models, digital credit providers prefer updating credit scores in real-time based on borrower repayment behavior (with a mean of 3.258) and periodically recalibrating scoring models based on portfolio performance data (with a mean of 2.5). Perhaps due to data availability and immediacy of behavioral signals make real-time updating of credit scores more attractive, as repayment behavior is readily observable, continuously generated, and directly linked to credit risk, enabling lenders to make quick, responsive adjustments with relatively lower complexity.

In addition, technical and operational capacity constraints play a role: real-time updates can be embedded into existing transactional systems with incremental automation, whereas effective recalibration requires stronger analytical capabilities, historical data integrity, and model validation frameworks, which many digital credit providers may only partially possess, leading to more moderate adoption.

In structuring loans & Limits, setting low initial credit limits for new borrowers and increasing them based on repayment history (Mean of 3.33) and differentiating loan limits by customer risk profile (mean of 3.3) are the popular strategies. Following closely is structuring repayment schedules to match borrowers' income cycles (mean of 2.95) and applying caps on total exposure to a single borrower or sector (mean of 2.924). This might imply that risk mitigation through incremental exposure control explains the dominance of low initial limits and risk-based differentiation, as these approaches directly manage default risk at origination using observable borrower behavior and simple segmentation, making them both effective and easy to operationalize.

Alternatively, alignment with borrower cash flows and portfolio risk management supports the moderate adoption of income-based repayment structuring and exposure caps or data and system capability constraints influence the hierarchy, since advanced tailoring of repayment schedules and sector-level exposure controls depend on reliable income data.

Even though use of Partnership/Credit guarantee schemes is least popular, partnering with credit bureaus to access and share borrower credit history (Mean of 2.87) and partnering with insurance providers to cover potential loan defaults (Mean of 2.096) as preferred approaches under this credit management strategy. Using government or development agency credit guarantee schemes and Co-lending or syndicated lending with other institutions to reduce exposure are the least preferred approaches with a mean of 1.2 for each. Most likely, the ease of integration and regulatory familiarity makes partnerships with credit bureaus and, to a lesser extent, insurance providers more attractive, as these arrangements are relatively standardized, widely recognized within existing credit infrastructure, and easier to operationalize for immediate risk assessment and mitigation.

In contrast, government guarantee schemes and co-lending arrangements often involve more complex approval processes, coordination challenges, and stricter eligibility or compliance requirements, which discourage widespread use. In addition, cost-benefit and flexibility considerations play a role: credit bureau data and insurance products offer more direct, scalable, and flexible risk management benefits, whereas syndicated lending and guarantee schemes may dilute control, involve higher transaction costs, or limit agility in decision-making, making them less appealing to digital credit providers focused on speed and operational independence.

For Automated Collection and Warning, Sending automated SMS or app notifications to remind borrowers of upcoming repayments is the most popular approach (with a mean of 3.63) followed by monitoring borrower transaction patterns to flag potential defaults (with a mean of 2.68) and then using predictive analytics to detect early signs of repayment difficulties (mean od 2.51) followed closely by integrating repayment reminders with borrowers' preferred payment channels (with a mean of 2.45).

This may be due to cost-effectiveness and ease of implementation, which make automated SMS/app reminders the most widely used, as they require minimal infrastructure, are highly scalable, and deliver immediate impact on repayment behavior. On the other hand, data and system integration constraints influence the moderate adoption of monitoring, analytics, and channel integration, since these require access to high-quality, real-time transactional data and seamless interoperability with payment platforms.

### 5.2.2 Organizational Factors Influencing the use of Credit Risk Management Strategies by Digital credit providers in Kenya

According to the multivariate analysis, the results report a weak association between dynamic credit scoring models and most independent variables, with coefficients indicating mixed positive and negative relationships. However, years of operation (positive, weak significance at 10%) and firm size (assets) (negative, significant at 5%) emerge as relevant predictors. The significant effects of years of operation and firm size suggest contrasting structural dynamics, where more experienced firms gradually adopt dynamic scoring due to learning effects and accumulated data, while larger firms may rely on established legacy systems or alternative risk frameworks, reducing their dependence on newer dynamic scoring approaches.

The associations between loan structuring practices and the independent variables are generally weak and statistically insignificant, indicating limited explanatory power of the predictors. The only marginally significant variable is credit management training (negative at 10%), suggesting that increased training may slightly reduce reliance on traditional structuring approaches, possibly due to the adoption of alternative techniques. However, this is not conclusive, given that the model diagnostics show that the model is not statistically significant and has low explanatory power, indicating a poor overall fit.

The model reveals weak and largely insignificant relationships between partnerships/credit guarantees and independent variables, with no strong predictors emerging. Although performing loans show a positive coefficient, it is not statistically significant, indicating no reliable influence. Overall, none of the independent variables significantly explains the variation in this dependent variable. This may suggest that low and uneven adoption across firms reduces explanatory power, since many digital credit providers do not actively use these mechanisms or apply them inconsistently,

The associations between automated systems and independent variables are also weak, with most variables showing no statistical significance. The only marginal influence is ROE (negative at 10%). Maybe institutional capacity and strategic priorities vary across digital credit providers, where some providers lack the technical expertise, financial resources, or risk appetite to implement these arrangements, while others prioritize faster, internally controlled risk management tools, leading to inconsistent application and limited overall variability in usage.

However, model diagnostics indicate that the model is not statistically significant and has a poor explanatory power implying that the included variables do not adequately explain the adoption of automated systems.

### 5.2.3 Management Perspectives on Credit Risk Management Strategies

19 respondents provided comments on the use of technology, such as AI-driven credit scoring or automated collections, that influenced the organization's ability to manage credit risk. The findings indicate that digital credit providers are increasingly leveraging artificial intelligence and machine learning to enhance credit risk management, particularly with alternative data and adaptive credit scoring models. The most cited application AI-driven models using non-traditional data such as mobile usage and transaction histories suggests a strong shift toward financial inclusion, especially for thin-file customers who lack formal credit histories. Additionally, the emphasis on improved accuracy of credit scoring and real-time decision-making reflects a transition from static, judgment-based lending to dynamic, data-driven risk assessment frameworks. These developments collectively point to greater efficiency, speed, and granularity in credit evaluation processes.

At a deeper level, the relatively lower frequency of responses on advanced applications such as fraud detection, NLP-based sentiment analysis, and dynamic credit limit adjustments suggests that while foundational AI tools are widely adopted, more sophisticated and integrated AI capabilities are still emerging. This uneven adoption may reflect differences in technological maturity, resource availability, and institutional capacity among lenders. Overall, the table demonstrates that AI is not only enhancing predictive accuracy but also enabling proactive risk monitoring and segmentation, thereby strengthening the overall credit risk management lifecycle.

62 responses were received on the challenges in implementing the credit risk management strategies. The results reveal that the implementation of AI-driven credit risk management is significantly constrained by both technical and regulatory challenges. The most prominent issues, limited availability of high-quality data and stringent data privacy regulations, highlight a fundamental tension between the need for rich data to power AI models and the requirement to protect consumer information. This suggests that data governance remains a critical bottleneck in digital lending. Furthermore, concerns around algorithmic bias, lack of explainability, and

cybersecurity risks indicate that institutions must balance innovation with ethical considerations, regulatory compliance, and system integrity.

From an operational perspective, challenges such as high implementation costs, integration with legacy systems, and shortages of skilled personnel underscore structural barriers that disproportionately affect smaller digital credit providers. The presence of model risk, rapidly changing borrower behavior, and regulatory uncertainty further complicates the deployment and sustainability of AI models. Collectively, these findings suggest that while the potential of AI in credit risk management is substantial, its effective implementation requires robust infrastructure, skilled human capital, and a clear regulatory framework to mitigate risks and ensure fairness and transparency.

41 responses were obtained on the changes or innovations that could further enhance credit risk management for digital credit lending in the future. The findings highlight a strong forward-looking emphasis on enhancing transparency, accountability, and customer protection in digital lending. The most frequently cited recommendation, adoption of explainable AI models, signals a growing recognition of the need to align technological innovation with regulatory expectations and ethical standards. Similarly, strengthening affordability assessments and aligning regulatory guidelines reflects a shift toward more responsible lending practices aimed at reducing over-indebtedness and improving financial stability. These priorities suggest that future innovations will not only focus on efficiency but also on sustainability and trust in the lending ecosystem.

In addition, the emphasis on data governance, clear pricing structures, and proactive monitoring mechanisms indicates a holistic approach to credit risk management that integrates technical, operational, and customer-centric considerations. Recommendations such as ethical collections, model validation, and stress testing further reinforce the importance of maintaining model robustness and adaptability in dynamic economic environments. Overall, the findings suggests that the future of digital credit risk management will be defined by a balance between advanced analytics, regulatory compliance, and enhanced consumer protection, ensuring both innovation and resilience in the sector.

## 5.3 Conclusion

### 5.3.1 Contribution to Theory

The findings strongly support the Resource-Based View (RBV) by demonstrating that digital credit providers prioritize internally controlled resources and capabilities, such as loan structuring, internal risk controls, and automated collection systems, which are valuable, scalable, and difficult to imitate. The emphasis on real-time data, AI-driven scoring, and accumulated experience (e.g., years of operation influencing adoption) reflects the RBV argument that firm-specific assets like data infrastructure, technological capability, and organizational learning drive competitive advantage (Barney, 1991; Wernerfelt, 1984). Additionally, the identified constraints, such as limited data quality, high implementation costs, and a shortage of skilled personnel, further reinforce that differences in resource endowments shape strategic choices and performance outcomes.

However, the findings also do not fully support RBV, as the weak and statistically insignificant relationships between most organizational variables and credit risk strategies suggest that internal resources alone are insufficient to explain adoption patterns. The low explanatory power of the regression models indicates that external environmental factors, such as regulatory requirements, market ecosystem maturity, and availability of partnerships, play a critical role, which RBV does not fully account for (Barney, 1991). Furthermore, the limited use of partnerships and credit guarantees suggests that firms are not effectively leveraging external or relational resources, challenging RBV extensions that emphasize inter-organizational resource integration (Wernerfelt, 1984).

The findings also support Prospect Theory, as the behavior of digital credit providers reflects a tendency toward risk aversion and loss minimization. The preference for conservative strategies, such as low initial credit limits, incremental exposure adjustments, and reliance on automated reminders, indicates that firms prioritize avoiding losses over pursuing higher but uncertain returns. Similarly, the cautious adoption of advanced AI models and limited engagement in partnerships suggests decision-making under uncertainty that aligns with the principle that agents overweight potential losses relative to gains (Kahneman & Tversky, 1979).

Conversely, the findings do not fully support Prospect Theory, as several decisions appear to be driven by rational, efficiency-oriented considerations rather than behavioral biases. For instance, the adoption of automated systems and real-time scoring is largely motivated by cost efficiency, scalability, and operational effectiveness, indicating deliberate optimization rather than purely loss-averse behavior. Moreover, the gradual uptake of advanced technologies and AI innovations suggests that firms are willing to take calculated risks when supported by sufficient resources and capabilities, which align more with rational choice frameworks than the bounded rationality emphasized in Prospect Theory (Kahneman & Tversky, 1979).

### 5.3.2 Contribution to Empirical Literature

Regarding the first objective on the use of credit risk management strategies, the findings support empirical studies by reinforcing the importance of internal credit risk management practices and digital tools in enhancing lending outcomes. For instance, the high adoption of loan structuring and automated collection systems aligns with evidence by Maina and Njeru (2023), who found that strong credit procedures and monitoring significantly improve loan recovery performance. Similarly, the use of real-time behavioral data in credit scoring supports the argument by Björkegren and Grissen (2017) that alternative digital data can improve credit risk prediction, particularly for underserved borrowers. The emphasis on automation and digital processes is also consistent with Allya et al. (2025), who show that fintech adoption contributes to improved loan performance through reduced non-performing loans.

However, the findings contradict the studies of Björkegren and Grissen (2017) and Yun (2025) that emphasize the growing importance of alternative data, AI, and collaborative ecosystems in credit risk management. The current findings reveal relatively low adoption of dynamic credit scoring models and partnerships/credit guarantees. Additionally, unlike Maina and Njeru (2023), who report strong and significant relationships between credit practices and performance, the current study finds weak and largely insignificant relationships between organizational factors and strategy adoption, indicating a gap between expected and actual outcomes.

The findings further extend the empirical literature in two ways**.** While prior studies broadly emphasize the effectiveness of digital tools and credit practices, this study adds depth by showing that firms prioritize simpler, internally controlled, and cost-effective strategies over more complex,

data-intensive, or collaborative approaches. Secondly, the findings extend Yun's (2025) work by empirically illustrating how challenges such as data limitations, system integration issues, and regulatory constraints concretely shape adoption patterns.

About the second objective, the findings support the empirical studies, but to a limited extent by confirming that certain organizational characteristics, particularly experience (years of operation) and, to some degree, firm size play a role in shaping the adoption of credit risk management strategies. This aligns with prior studies which argue that organizational maturity, governance structures, and resource capacity influence risk management adoption (Ferilli, 2024; Mandimutsira, 2015). For instance, the positive association between years of operation and the use of dynamic credit scoring reflects learning effects and accumulated capabilities, consistent with the view that firms build risk management competence over time. Additionally, the role of training and technological capacity, though weak, echoes findings that human capital and IT infrastructure are important enablers of risk management systems (Okello, 2012; Gambacorta et al., 2024).

However, the findings contradict empirical studies in several ways. While earlier studies emphasize strong and significant relationships between governance, firm size, institutional pressures, and the adoption of risk management frameworks (Ferilli, 2024; Sun, 2024), the current findings reveal predominantly weak and statistically insignificant associations across most variables. For example, governance-related variables such as board size, credit committees, and auditor type do not significantly explain the adoption of credit risk strategies, contrary to expectations from prior literature. Similarly, while previous studies suggest that larger and more complex firms are more likely to adopt sophisticated risk systems (Mandimutsira, 2015), the negative relationship between firm size and dynamic credit scoring in this study challenges that assumption, indicating that larger firms may rely on legacy systems rather than newer innovations.

The findings extend the empirical literature in several ways. Unlike prior studies that emphasize structural and governance determinants, this study highlights the importance of strategic priorities, uneven adoption, and ecosystem constraints in shaping outcomes. The weak explanatory power of the models suggests that factors such as regulatory environment, market maturity, and firm-level strategic choices may be more influential than traditional organizational variables. Additionally, the findings reveal that adoption is fragmented and inconsistent across firms, thereby extending existing literature by demonstrating that, in emerging digital lending contexts, risk management

practices are not always systematically driven by governance or size, but rather by practical considerations such as cost, capability, and operational flexibility.

Finally, about objective 3 on management perspectives, the findings support empirical studies by reinforcing the central role of management perspectives, attitudes, and strategic priorities in shaping credit risk management practices. The increased adoption of AI-driven credit scoring, automation, and alternative data usage demonstrates that management views credit risk management as a strategic function, consistent with evidence that positive managerial attitudes significantly enhance CRM adoption (Ntiamoah et al., 2019). Furthermore, the emphasis on improved accuracy, real-time decision-making, and proactive monitoring aligns with findings that management incentives and oversight influence the effectiveness of screening and credit evaluation processes (Cole et al., 2020). This suggests that leadership commitment to innovation and efficiency continues to drive the evolution of credit risk management practices.

However, the findings also contradict empirical studies to some extent, particularly regarding the consistency and effectiveness of management-driven CRM adoption. While prior studies suggest strong and direct relationships between management attitudes, incentives, and robust CRM implementation (Ntiamoah et al., 2019; Cole et al., 2020), the current findings reveal uneven adoption of advanced AI capabilities and significant operational challenges, including data limitations, regulatory constraints, and a lack of skilled personnel. These constraints indicate that even when management is positively inclined toward CRM, external and structural barriers can limit effective implementation. Additionally, the relatively low adoption of advanced tools such as NLP and fraud detection suggests that management influence alone may not be sufficient to ensure comprehensive or sophisticated CRM systems in practice.

The findings further extend the empirical literature in several ways. Unlike earlier studies that primarily focus on attitudes and incentive structures, this study highlights how management must now navigate complex trade-offs between innovation, regulation, and ethical considerations, particularly in the use of AI and alternative data. The identification of challenges such as algorithmic bias, data privacy, and cybersecurity risks extends existing literature by emphasizing the evolving responsibilities of management beyond traditional credit oversight. Moreover, the forward-looking emphasis on explainable AI, data governance, and customer protection demonstrates that management perspectives are increasingly aligned with sustainability and

regulatory compliance, thereby broadening the scope of CRM from operational efficiency to holistic, responsible financial management.

### 5.3.3 Contribution to Practice

The findings suggest several important implications for stakeholders in Kenya and the broader region. First, for digital credit providers, the heavy reliance on internal, simple risk management tools (such as loan structuring and automated reminders) implies a need to strategically invest in more advanced capabilities, particularly AI, alternative data analytics, and model validation, to remain competitive and improve predictive accuracy over time.

Second, for regulators and policymakers, the identified constraints around data quality, privacy, and uneven adoption highlight the need to strengthen regulatory frameworks, promote standardized data-sharing ecosystems, and provide clearer guidance on the use of AI and alternative data in credit risk management to enhance both innovation and consumer protection.

Third, for technology providers and fintech partners, the low adoption of advanced analytics and partnerships indicates a significant market opportunity to develop scalable, cost-effective, and interoperable solutions that address integration challenges and reduce implementation costs for lenders.

Fourth, for investors and development partners, the variability in adoption and the weak link between organizational factors and strategy usage suggest the importance of supporting capacity building, particularly in data infrastructure, technical skills, and governance, to improve the effectiveness and sustainability of digital lending models.

Finally, for borrowers and consumer advocacy groups, the growing use of automation and AI underscores the need for stronger transparency, fairness, and ethical lending practices, including explainable credit decisions, responsible pricing, and safeguards against over-indebtedness, to build trust and ensure inclusive financial access.

## 5.4 Limitations of the Study

One limitation of the study stems from the reliance on a semi-structured online questionnaire as the primary data collection tool. Although this method enhances efficiency and allows for standardized data collection across geographically dispersed respondents, it restricts the depth of inquiry compared to fully qualitative approaches such as interviews or focus groups. The absence of interviewer facilitation limits opportunities for probing, clarification, and follow-up, which may result in superficial or misinterpreted responses. Additionally, the online modality may introduce selection bias by favoring respondents who are more digitally engaged, potentially excluding relevant stakeholders within Kenya's diverse digital credit ecosystem.

The response rate of 93 out of 153 targeted participants, while improved, still presents methodological concerns. This represents approximately a 61% response rate, which, although acceptable in survey research, leaves room for non-response bias. The views and practices of non-respondents may systematically differ from those who participated, thereby affecting the representativeness of the findings.

A further limitation was the relatively low level of engagement with the unstructured sections of the questionnaire. Open-ended responses are essential for capturing context-specific insights, innovative practices, and nuanced perspectives on credit risk management strategies. However, fewer responses in these sections limit the scope for comprehensive qualitative analysis and thematic development. This imbalance may result in an over-reliance on structured responses, potentially overlooking critical dimensions of digital lending practices that are not captured within predefined options.

Finally, the use of a multinomial regression model introduces constraints associated with its underlying assumptions. These include the independence of irrelevant alternatives (IIA), the absence of multicollinearity among explanatory variables, and the requirement for adequate sample size across outcome categories. In practice, these assumptions may not fully hold, particularly in studies involving complex behavioral and institutional factors such as credit risk management strategies. Any violation of these assumptions can lead to biased or inefficient parameter estimates, thereby affecting the reliability and interpretability of the model's results. The response rate, was however, sufficient to reduce biasness.

## 5.5 Recommendations for further studies

Further studies can be conducted based on context (other countries or jurisdictions), a different population (commercial banks that also engage in digital lending and operate under different regulatory environments), and establish some of the key findings.

For example, for investors and development partners, the variability in adoption and the weak link between organizational factors and strategy usage suggest the importance of supporting capacity building, particularly in data infrastructure, technical skills, and governance, to improve the effectiveness and sustainability of digital lending models. Further studies could evaluate the key priority areas that are required to improve credit risk management strategies for digital lending.

## 5.6 Summary of the Chapter

Chapter Five is the final chapter and covers the discussions, conclusions, limitations, and recommendations for further studies. The introduction section provided the objectives of the study, while the discussions highlighted the results and findings from chapter four, it also contributed to knowledge (theory and empirical studies). The conclusion section provided the implications for theory, academic, and practice. Finally, the limitations section highlighted challenges with data collection and tools, and the study recommended further areas of research.

VT OMNES VNVM SINT

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# APPENDICES

## Appendix I: Letter of Introduction

Dear Participant,

**Ref: Request for Participation in Academic Study: ORGANIZATIONAL FACTORS INFLUENCING THE CREDIT RISK MANAGEMENT STRATEGIES BY DIGITAL CREDIT PROVIDERS IN KENYA**

I trust this message finds you well. My name is Hanafi Ali, a Master's student in Development Finance at Strathmore University Business School. I am conducting an academic study titled **"Organizational Factors Influencing the Credit Risk Management Strategies by Digital Credit Providers in Kenya."** The purpose of this study is to examine the strategies and practices employed by digital credit providers to mitigate and manage credit risk within Kenya's digital lending environment, particularly in the context of heightened regulation by the Central Bank of Kenya.

You have been identified as a suitable participant due to your knowledge and/or experience in digital credit services. I kindly request your participation by providing responses to the research questions in the attached questionnaire/interview guide. Your contribution will be valuable in supporting the understanding of credit risk management practices within the sector and in enriching academic and policy discussions on digital credit services in Kenya.

Please note that participation in this study is completely voluntary. All information provided will be handled with strict confidentiality and will be used exclusively for academic purposes. Your identity (and that of your institution, where applicable) will not be revealed in the research report, and all responses will be reported in aggregated form to ensure anonymity.

If you consent to participate, please complete and return the questionnaire at your earliest convenience. Should you require any clarification regarding the study, kindly feel free to contact me.

Thank you in advance for your time and support.

Yours Sincerely

Hanafi S. A. Ali

Student Reg No. 171681

## Appendix II: Questionnaire

**Instructions**

Kindly complete the questionnaire as per the questions given in each section. Please tick the appropriate options and write your responses in the spaces provided where applicable.

**Confidentiality**

All information provided will be treated with strict confidentiality. No reference will be made to any individual(s) or organization in the study report.

**Part A: Respondent Details**

1. Title in the organization_____
2. No of years in Organization_____
3. Industry Experience_____

**Part B: Organization Details**

1. Years in operation_____
2. Number of Directors on the Board_____
3. Is there a credit committee of the Board?

| | |
|---|---|
| Yes | |
| No | |

4.Estimated Return on Equity (profit after tax/ Equity) in % _____

5.Estimated Size of Performing Loans to Total Loans in %_____

6. Estimated Total Size in Millions of Shillings_____

7.Is Your Auditor among the Big Five (PWC, Earnest & Young, Deloitte, KPMG and PKF)?

| | |
|---|---|
| Yes | |
| No | |

8.Estimate number of trainings on credit risk management per year_____

9.Number of technologies used by the firm on credit risk management _____

**Part C: Use of Credit Risk Management Strategies**

1.To what extent is the organization using the following credit risk management strategies?

1 Not at all – Strategy is not used at all in the organization.
2 To a small extent – Strategy is rarely used or used in a very limited way.
3 To a moderate extent – Strategy is sometimes used, but not consistently.
4 To a great extent – Strategy is frequently used and is part of standard operations.
5 To a very great extent – Strategy is fully integrated and systematically applied across operations.

| | 1.Not at all | 2.To a small extent | 3.Moderate extent | 4.Great extent | 5.Very Great extent |
|---|---|---|---|---|---|
| Dynamic Credit Scoring Models | | | | | |
| Loan Structuring & Limits | | | | | |
| Partnerships/credit guarantees | | | | | |
| Automated collections and warning systems | | | | | |

**Indicate any other credit risk management strategy not included above**

_____

_____

_____

2. To what extent does your organization use the following dynamic credit scoring practices?

| | 1. Not Used | 2. Partially Used | 3. Mostly Used | 4. Fully Used |
|---|---|---|---|---|
| Updating credit scores in real-time based on borrower repayment behavior | | | | |
| Integrating alternative data (e.g., mobile money transactions, utility payments) into credit scoring | | | | |
| Using AI/ML algorithms to adjust scoring criteria in response to market changes | | | | |
| Periodically recalibrating scoring models based on portfolio performance data | | | | |
| Segmenting borrowers dynamically for risk-based loan offers and limits | | | | |

Indicate any other dynamic credit scoring practices not provided above

_____

_____

_____

3. To what extent does your organization use the following Loan Structuring & Limits practices?

| | 1.Not Used | 2.Partially Used | 3.Mostly Used | 4. Fully Used |
|---|---|---|---|---|
| Setting low initial credit limits for new borrowers and increasing them based on repayment history | | | | |
| Offering shorter loan tenures for first-time borrowers to minimize exposure | | | | |
| Differentiating loan limits by customer risk profile | | | | |
| Structuring repayment schedules to match borrowers' income cycles | | | | |
| Applying caps on total exposure to a single borrower or sector | | | | |

Indicate any other Loan Structuring & Limits not included above

_____

_____

_____

4. To what extent does your organization use the following Partnerships/credit guarantees practices?

| | 1.Not Used | 2.Partially Used | 3.Mostly Used | 4. Fully Used |
|---|---|---|---|---|
| Partnering with credit bureaus to access and share borrower credit history | | | | |
| Collaborating with fintech firms or banks to share risk and customer data | | | | |
| Using government or development agency credit guarantee schemes | | | | |
| Partnering with insurance providers to cover potential loan defaults | | | | |
| Co-lending or syndicated lending with other institutions to reduce exposure | | | | |

Indicate any other Partnerships/Credit Guarantee Practices not included above

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5. To what extent does your organization use the following Automated Collections and Warning Systems?

| | 1.Not Used | 2.Partially Used | 3.Mostly Used | 4. Fully Used |
|---|---|---|---|---|
| Sending automated SMS or app notifications to remind borrowers of upcoming repayments | | | | |
| Using predictive analytics to detect early signs of repayment difficulties | | | | |
| Automating follow-up actions for overdue accounts (e.g., calls, emails) | | | | |
| Monitoring borrower transaction patterns to flag potential defaults | | | | |

| | | | | |
|---|---|---|---|---|
| Integrating repayment reminders with borrowers' preferred payment channels (e.g., mobile money push prompts) | | | | |

Indicate any other Automated Collections and Warning Systems not included above

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6.Indicate the extent to which the following credit risk management strategies are effective?

| | 1.Not effective | 2.Effective to a small extend | 3. Effective moderately | 4.Effective to a great extent | 5.Effective to a very great extent |
|---|---|---|---|---|---|
| Dynamic Credit Scoring Models | | | | | |
| Loan Structuring & Limits | | | | | |
| Partnerships/credit guarantees | | | | | |
| Automated collections and warning systems | | | | | |

Comment on the selection of your responses

_____

_____

_____

7. How has the use of technology, such as AI-driven credit scoring or automated collections, influenced your organization's ability to manage credit risk?

8. What are the main challenges you face when implementing these credit risk management strategies in the digital lending environment?

9. In your view, what changes or innovations could further enhance credit risk management for digital credit lending in the future?

## Appendix III: List of Digital Credit Providers (DCPs)

| No | DCP |
|---|---|
| 1 | Abito Limited |
| 2 | Absolute Credit Kenya Ltd |
| 3 | Adroit Credit Limited |
| 4 | Ajax Credit Limited |
| 5 | Ambush Capital Limited trading under FlashPesa |
| 6 | Anjoy Credit Limited |
| 7 | Asap Credit Limited |
| 8 | Asante FS East Africa Limited |
| 9 | Aspire Lending Limited |
| 10 | Autocheck Limited |
| 11 | Aventus Technology Limited |
| 12 | Avenews Ke Ltd |
| 13 | AVL Capital Ltd |
| 14 | Azura Credit Limited |
| 15 | Bimas Kenya Limited |
| 16 | Bossrich Credit Limited |
| 17 | BRAC Kenya Company Limited |
| 18 | Brisk Credit Limited |
| 19 | Bytech Credit Limited |
| 20 | Ceres Tech Limited |
| 21 | Chapeo Capital Limited |
| 22 | Chelete Credit Limited |
| 23 | Chime Capital Limited |
| 24 | Colkos Enterprises Limited |
| 25 | Creditarea Capital Limited |
| 26 | Decimal Capital Limited |
| 27 | Dexintec Kenya Limited |
| 28 | Dime Credit Limited |
| 29 | East African Futures Company Limited |
| 30 | Easy Asset Management Limited |
| 31 | Easyways Credit Limited |
| 32 | ED Partners Africa Limited |
| 33 | EDOMX Limited |
| 34 | Ellegant Credit Limited |
| 35 | Elevate Credit |
| 36 | Extend Money Services Limited |
| 37 | Fabilo Credit Ltd |
| 38 | Factorhouse Limited |
| 39 | Fahari Point Capital Limited |
| 40 | Fantom Capital Limited |
| 78 | Mayflower capital |
| 79 | Marble Capital Solutions Limited |
| 80 | MCF 2 Kenya Limited |
| 81 | Maxxton Enterprise Ltd |
| 82 | Mednow Capital |
| 83 | Mint Credit Limited |
| 84 | Milhan Access Capital Limited |
| 85 | MFS Technologies Limited |
| 86 | MKM Capital Limited |
| 87 | M-Kopa Loan Kenya Limited |
| 88 | Mogo Auto Limited |
| 89 | Mkulima Pay Ltd |
| 90 | Modesty Credit Ltd |
| 91 | Momentum Credit Limited |
| 92 | Moto Hope Capital Limited |
| 93 | Mwanzo Credit Limited |
| 94 | Moneza Ltd |
| 95 | Mycredit Limited |
| 96 | MyWagepay Limited |
| 97 | Mwananchi Credit Limited |
| 98 | Mular Credit Limited |
| 99 | Musoni Capital Limited |
| 100 | Natal Tech Limited |
| 101 | Ngao Credit Limited |
| 102 | Nawiri African Sprouts Ltd trading as Fast Credi |
| 103 | Newark Frontier Limited |
| 104 | ODI Credit Limited |
| 105 | Otas Credit Limited |
| 106 | Numida Technologies Limited |
| 107 | Okolea International Limited |
| 108 | Opal Quick Limited |
| 109 | Payablu Credit Limited |
| 110 | Pembeni Cash Limited |
| 111 | Pesaglow Capital Limited |
| 112 | Pesakuu Credit Limited |
| 113 | Pezesha Africa Limited |
| 114 | Platinum Credit Limited |
| 115 | Phoenix Capital Limited |
| 116 | Pi Capital Limited |
| 117 | Premier Credit Limited |

41 Fezotech Kenya Limited
42 Finberry Capital Ltd
43 Finboom Credit Kenya Limited
44 Fincorp Credit Limited
45 Finsell Limited
46 Fortune Credit Limited
47 Fourth Generation Capital Limited
48 Frictionless Enterprises Limited
49 Futureinno Digital Tech Limited
50 Getcash Capital Limited
51 Giando Africa Limited (Trading as Flash Credit Africa)
52 Girls First Kenya Limited
53 Granary Capital Limited
54 Hanis Capital
55 Hela Capital Limited
56 Helium Credit Limited
57 Inventure Mobile Limited (Trading as Tala)
58 Inspire Credit Limited
59 Ismuk Credit Limited
60 Jijenge Credit Limited
61 Jumo Kenya Limited
62 Kifedha Ltd
63 Kikwetu Credit Ltd
64 Kweli Smart Solutions Limited
65 Lasiri Capital Limited
66 Leaf Limited
67 Leja Ltd
68 Lenana Innovative Solutions Limited
69 Letshego Kenya Ltd
70 Spot It Limited
71 Lipa Later Limited
72 Little Pesa Limited
73 Loan Plus Ltd
74 Lobelitec Credit Limited
75 LockBx Limited
76 Maralal Ledger Limited
77 Longitude Capital Limited
118 Puphik Credit Limited
119 Progressive Credit Limited
120 Radi Credit Limited
121 Reazilla DCP Limited
122 Rewot Ciro Limited
123 Risine Credit Limited
124 Senti Capital Limited
125 Sevi Innovation Limited
126 Simplepay Capital Limited
127 Siti Mobility Technologies Limited
128 Sokohela Limited
129 Simbageld Ltd
130 Sipranda Capital Ltd
131 Sure Cred Capital Limited
132 Spectrum Capital Ltd
133 Spread Capital Ltd
134 Steadfast Credit Ltd
135 Stride Credit Limited
136 Suffice Limited
137 Tanir Credit & Accounting Services Limited
138 Tenakata Enterprises Limited
139 Tip-Point Capital Limited
140 Tentacorp Holdings Limited
141 Tinycost Credit Kenya Limited
142 Treasure Store Limited
143 UbaPesa Limited
144 Umoja Fanisi Limited
145 Zanifu Limited
146 Unifi Credit Limited
147 Unidirect Limited
148 Wabema Credit Ltd
149 Watu Credit Ltd
150 Zamaradi Capital Credit
151 Zaidi Pato Limited
152 Zenka Digital Limited
153 Zillions Credit Limited

## Appendix IV: Ethical Approvals

### Strathmore University

Strathmore UNIVERSITY

**27th March 2026**

Mr Ali Hanafi,
hanafi.sheikh@strathmore.edu

Dear Mr Ali,

**RE: Organizational Factors Influencing the Credit Risk Management Strategies by Digital Credit Providers in Kenya**

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC3466/26**. The approval period is from **27th March 2026 to 26th March 2027**.

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification
iv. Any changes, anticipated or otherwise, that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

**Mr Ambrose Rachier,**
**Chairperson; SU-ISERC**

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Email admissions@strathmore.edu www.strathmore.edu

**NACOSTI**

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 539629

Date of Issue: 18/April/2026

## RESEARCH LICENSE



This is to Certify that Mr.. ABDI ALI HANAFI SHEIKH of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: ORGANIZATIONAL FACTORS INFLUENCING THE CREDIT RISK MANAGEMENT STRATEGIES BY DIGITAL CREDIT PROVIDERS IN KENYA for the period ending : 18/April/2027.

License No: NACOSTI/P/26/4188208

539629

Applicant Identification Number

Ag. Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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See overleaf for conditions