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DETERMINANTS OF EMERGING TECHNOLOGY ADOPTION (ARTIFICIAL INTELLIGENCE, BLOCKCHAIN AND MACHINE LEARNING) IN CREDIT ANALYIS AMONG DEPOSIT-TAKING SACCOS IN KENYA

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(168415)

A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF MASTER OF BUSINESS ADMINISTRATION AT STRATHMORE UNIVERSITY

NAIROBI, KENYA

MAY 2025

DECLARATION

I confirm that this work has not been submitted before for a degree at Strathmore University or any other university. To the best of my knowledge, it contains no material previously published or authored by someone else, except where proper citation is made in the dissertation itself.

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Signature:

Approval

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Faculty Affiliation: Accounting & Finance

Institution: Strathmore Business School

Signature:

DEDICATION

This work is dedicated to my beloved family, whose unwavering love, patience, and encouragement have been my greatest source of strength throughout this academic journey.

To my parents, for instilling in me the value of education and perseverance.

To my friends and colleagues, for their constant support and understanding.

And to everyone who believed in me even when the journey seemed long and challenging—this work is a testament to your faith in me.

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ABSTRACT

Emerging technologies, including artificial intelligence (AI), blockchain, and machine learning (ML), are significantly transforming credit analysis; however, their adoption among deposit-taking SACCOs in Kenya remains limited. This study sought to examine the factors influencing the adoption of these emerging technologies in credit analysis among DTSs in Kenya. The specific objectives were to establish effect of financial capacity, board characteristics and technological characteristics on the adoption of emerging technologies in credit analysis. The study was guided by the Technology-Organization-Environment (TOE) theory. The descriptive cross-sectional design was used in this study wherein primary and secondary data was collected from 110 DTSs. Primary data was collected using questionnaires administered to managers of the DTSs in Kenya, including key roles such as credit managers, information technology managers, and operations managers, which focused on technology characteristics and extent of adoption. Secondary data was collected from 2024 annual reports of DTSs, and were used to obtain data on financial and board characteristics. Regression results confirmed these patterns, with board characteristics and financial capacity emerging as significant predictors, while technology characteristics showed no significant independent effect. The findings indicate that SACCOs with stronger financial positions (higher profitability, better asset quality, and capital adequacy) and robust board structures (independent, diverse boards) were more likely to adopt advanced technologies, regardless of their perceptions about the technologies themselves. These results have important theoretical and practical implications. Theoretically, they support but qualify the Technology-Organization-Environment (TOE) framework, demonstrating that organizational factors outweigh technological considerations in resource-constrained environments like SACCOs. Practically, the findings suggest that efforts to promote digital transformation should prioritize building financial capacity and board structures before addressing technological perceptions. Policymakers and SACCO managers should focus on improving financial management practices, strengthening board independence and diversity, and securing capital for technology investments. The study was limited to three categories of determinants and focused only on licensed deposit-taking SACCOs in Kenya using a cross-sectional design. Despite this, the study contributes to existing knowledge by extending the TOE framework to SACCOs, highlighting the primacy of organizational factors over technological perceptions in low-resource settings, and integrating both primary and secondary data to provide a comprehensive view of adoption dynamics.

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ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
CAGR	Compound Annual Growth Rate
CIPIT	Centre for Intellectual Property and Information Technology Law
CRB	Credit Reference Bureau
KBA	Kenya Bankers Association
ML	Machine Learning
NACOSTI	National Commission for Science, Technology and Innovation
NPL	Non-performing Loans
SACCO	Savings and Credit Cooperative Organization
SASRA	Sacco Societies Regulatory Authority
SME	Small and Medium Enterprises
SPSS	Statistical Package for Social Sciences
TOE	Technology-Organization-Environment

DEFINITION OF KEY TERMS

Extent of Adoption of Emerging Technologies

This is defined as the degree to which SACCOs accept, integrate, and utilize artificial intelligence, blockchain, and machine learning technologies in credit analysis processes (Hassan, 2024; Rahman et al., 2021; Schuetz & Venkatesh, 2020)

Artificial Intelligence (AI)

AI refers to the simulation of human intelligence in machines that are programmed to think, learn, and make decisions, by using algorithms and data to identify patterns, solve problems, and perform tasks that usually require human intervention, such as decision-making in credit analysis (Mogaji & Nguyen, 2021).

Blockchain

Blockchain is a decentralized, distributed digital ledger technology that is used for recording transactions across multiple computers in a way that ensures that the data is immutable, transparent and secure. It is used in various applications, including verifying transactions, preventing fraud, and ensuring data integrity in credit analysis by creating tamper-proof records of financial transactions (Nobanee et al., 2024).

Credit Analysis

Credit analysis is the process of evaluating a borrower's creditworthiness and ability to repay a loan. It involves examining financial information, such as income, debts, and credit history, as well as qualitative factors like the borrower's business stability and market conditions (Batchu, 2023).

Deposit-Taking SACCOs (Savings and Credit Cooperative Societies (DTS)

DTS are cooperative societies that accept deposits from their members and provide loans or credit facilities to those members (SASRA, 2024).

Financial capacity

Financial capacity refers to the economic strength and resource availability of an organization that influences its ability to make strategic decisions, including technology adoption (Noriega et al., 2023).

Board characteristics

Board characteristics refers to size, independence and diversity of the board (Noriega et al., 2023).

Machine Learning (ML)

ML a subset of AI that enables computers to automatically learn from data and then improve their performance over time on their own without programming. In the context of credit analysis, ML algorithms can analyze large datasets to predict creditworthiness, detect fraud, and assist in loan decision-making processes by learning from historical data (Maehara et al., 2024).

Organizational Factors

Organizational factors refer to the internal elements of an organization that influence its ability and willingness to adopt emerging technologies (Jöhnk et al., 2021).

Technology Characteristics

Technology characteristics refer to the features and attributes of an emerging innovation that affect its adoption and implementation (Neumann et al., 2024).

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Emerging technologies, including artificial intelligence (AI), blockchain, and machine learning (ML), are significantly transforming credit analysis in the financial services sector (Paramesha et al., 2024). AI enables institutions to analyze huge amounts of data, identifying patterns that improve credit scoring accuracy and minimize default risks (Paramesha et al., 2024). Blockchain enhances transparency and security in credit transactions by providing immutable records, which reduces fraud and increases trust in lending processes (Nobanee et al., 2024). Moreover, ML algorithms adapt to emerging data over time; hence, offering valuable predictive insights that can refine decision-making in credit risk management (Paramesha et al., 2024). These innovations also facilitate the incorporation of alternative data sources, such as social media pages and utility payments, to assess borrowers' creditworthiness, thus fostering financial inclusion (Walambe et al., 2021). Taken together, these emerging technologies are not only revolutionizing traditional credit practices but also enabling financial institutions to achieve greater operational efficiency and inclusivity.

Globally, in developed countries such as the U.S and the U.K, financial institutions are progressively adopting AI, blockchain, and ML to enhance credit analysis processes (Nwachukwu & Olatunji, 2023). In 2023, the financial services industry invested an estimated $35 billion in AI, with the banking sector leading by accounting for approximately $21 billion of this expenditure (Statista, 2024). Notably, 75 percent of financial institutions have integrated AI into their operations, with over half utilizing this technology for automated decision-making (Congressional Research Service, 2024). In addition, the AI in Lending Market is anticipated to grow from $7 billion in 2023 to $58.1 billion by 2033 – this translates to a compound annual growth rate (CAGR) of 23.5 percent (Market.us, 2024). In the United States, a report by the Congressional Research Service (2024) highlights the evolving adoption of AI and ML in financial services, and notes that these technologies are being employed to enhance efficiency and decision-making in credit risk assessments. Similarly, in the United Kingdom, Market.us (2024) revealed that 75% of financial firms are already utilizing AI, and an additional 10% are preparing to implement this technology in the near future. These statistics underscore a significant trend: financial institutions in developed economies are increasingly leveraging AI, blockchain, and ML to improve credit risk assessments, streamline operations, and maintain a competitive edge in the evolving financial landscape.

In the African region, the adoption of AI, blockchain, and ML in financial services is progressing, although at a slow pace. South Africa is at the forefront, with substantial investments in AI technology over the past decade. In Nigeria, the AI market is projected to grow by 27.08% between 2025 and 2030, reaching a market volume of $4.64 billion by 2030 (Statista, 2023). However, challenges such as inadequate policy frameworks, ethical considerations, and a lack of structured data ecosystems continue to impede widespread adoption across the continent (Centre for Intellectual Property and Information Technology Law [CIPIT], 2023). Despite these challenges, the trend indicates a gradual yet steady integration of these technologies into Africa's financial sectors.

Locally, in Kenya, the adoption of AI, blockchain, and ML into financial services is slowly advancing despite the fact that the AI market in Kenya is projected to grow by 27.33% between 2025 and 2030, reaching a market volume of $1.07 billion by 2030 (Statista, 2023). A study by the Kenya Bankers Association (KBA) highlights the increasing importance of AI in supporting business operations, particularly in risk management and revenue growth within the banking sector (Theuri & Olukuru, 2022). Additionally, Bhatti (2019) reported that Kenyan banks have begun implementing AI-driven solutions, such as chatbots, to enhance customer service and operational efficiency. Despite these advancements, challenges persist, including a lack of relevant data for developing AI systems and the lack of a comprehensive regulatory framework governing AI adoption in the country (Paradigm Initiative, 2022). The adoption of emerging technologies in credit analysis, specifically artificial intelligence (AI), blockchain, and machine learning (ML), is at a nascent stage, particularly within the SACCO sector (Nyabwari & Kimutai, 2024). While commercial banks and fintech firms have begun integrating AI-driven tools such as chatbots and predictive credit scoring models, most deposit-taking SACCOs (DTSs) remain reliant on manual credit assessment methods.

According to the 2023 SACCO Supervision Report by SASRA, over 50% of DTSs have not implemented basic digital platforms, such as mobile applications or internet banking systems, let alone advanced technologies like AI or blockchain (Nyabwari & Kimutai, 2024). These factors suggest that while there is a growing interest in integrating AI and ML into credit risk management, widespread adoption is still low.

There are indications that credit analysis among Kenyan SACCOs has not been as robust as required; hence, leading to concerns over loan defaults and financial instability (Nyabwari & Kimutai, 2024). Reports from SASRA have highlighted rising non-performing loans (NPLs) within the SACCO sector, which suggests weaknesses in borrower assessment and risk management. In 2016, the rate of NPLs was 5.23%, which increased to 6.14 percent in 2017, 6.3 percent in 2018, 6.15 percent in 2019, 8.39 percent in 2020 and 8.86 percent in 2021 (Nyabwari & Kimutai, 2024). Many SACCOs still rely on traditional, manual methods of credit evaluation, which are often subjective and inconsistent (Nyabwari & Kimutai, 2024). The lack of standardized credit scoring models makes it difficult to assess the true creditworthiness of members, leading to lending decisions that are based more on relationships or past savings history rather than actual risk assessment.

Furthermore, some SACCOs have struggled with limited access to credit information, as not all are fully integrated with the Credit Reference Bureau (CRB) system (SASRA, 2024). This means they may issue loans without a clear understanding of a borrower's financial obligations elsewhere, increasing the risk of default. The use of collateral-based lending rather than data-driven credit analysis also restricts access to loans for members who may not have physical assets but have strong repayment potential based on other financial behaviors (SASRA, 2024).

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These challenges indicate a clear need for modernization in credit analysis practices. It is crucial to recognize that traditional credit assessment approaches are time-consuming, prone to human error, and inadequate in identifying credit risk accurately (Nyabwari & Kimutai, 2024). The increasing complexity of financial transactions and member needs requires SACCOs to adopt more data-driven, automated, and AI-enhanced credit analysis tools to improve efficiency, reduce defaults, and enhance financial inclusion.

Existing studies on the adoption of emerging technologies in credit risk management have predominantly focused on commercial banks (Bhatti, 2019; Rahman et al., 2021), leaving a significant gap in understanding their application within deposit-taking SACCOs (DTSs), particularly in Kenya. DTSs are pivotal in the country's financial ecosystem, providing essential financial services to underserved populations, including savings and credit facilities (SASRA, 2024). Exploring the factor that affect the adoption of these technologies is key to addressing these barriers and developing targeted interventions to enhance adoption. By focusing on SACCOs, this research contributed to a more inclusive financial system in Kenya, ensuring that these institutions can leverage advanced technologies to improve credit analysis, mitigate risks, and enhance operational efficiency. The study focuses on three key categories of determinants - financial capacity, board characteristics, and technology characteristics - because they represent the core elements that shape decision-making and technology adoption within financial institutions, including SACCOs.

1.1.1 Adoption of Emerging Technologies

Schuetz and Venkatesh (2020) describe the adoption of emerging technologies as the choice to acquire and use a new invention or innovation. Frost (2020) defined the adoption of emerging technologies as the process in which individuals or organizations develop an attitude towards a new innovation, followed by deciding on whether or not to adopt, and then finally implementing the idea. For this study, the adoption of emerging technologies was defined as the process by which these institutions accept, integrate, and utilize AI, blockchain, and ML technologies in credit analysis (Hassan, 2024; Rahman et al., 2021; Schuetz & Venkatesh, 2020).

Credit analysis is defined as the process of appraising the creditworthiness of a borrower to establish their ability and likelihood to repay a loan or meet financial obligations (Rane et al., 2023). This process of credit analysis involves assessing various factors, such as the financial history of the borrower, their income, assets, liabilities, credit score, and market conditions, to estimate the degree of risk of lending to them (Yang et al., 2022). In this study, the adoption of emerging technologies was operationally defined as the extent to which SACCOs use AI, blockchain and ML in credit analysis processes, which will be measured using a 5-point Likert scale.

1.1.2 Financial Capacity

Financial capacity has been selected for this study because a SACCO's financial health determines its capacity to invest in and sustain emerging technologies (Jöhnk et al., 2021). Financially stable SACCOs are more likely to adopt advanced credit analysis tools, while those with weaker financial performance may struggle to afford such investments. Financial capacity refers to the economic strength and resource availability of an organization that influences its ability to make strategic decisions, including technology adoption (Noriega et al., 2023). This study measures financial capacity using profitability, which assesses a SACCO's ability to generate earnings, asset quality, which reflects the proportion of non-performing loans; and capital adequacy, which measures the SACCO's financial cushion to absorb potential losses (Jöhnk et al., 2021).

1.1.3 Board Characteristics

Board characteristics were included in this study because the leadership structure of a SACCO plays a critical role in shaping its strategic direction and decision-making, particularly regarding innovation (Eskandarany, 2024). Board characteristics refers to size, independence and diversity of the board (Noriega et al., 2023). Strong boards ensure that SACCOs make informed, unbiased, and well-structured decisions about adopting emerging technologies (Eskandarany, 2024). This study examined board characteristics through board size, which affects decision-making efficiency and access to diverse expertise; board independence, which determines the level of oversight and objectivity in decision-making; and board diversity, which ensures a mix of perspectives, experiences, and professional backgrounds that can encourage the adoption of innovative solutions (Jöhnk et al., 2021).

The selection of the three board characteristics, size, independence, and diversity, was guided by both theoretical grounding and empirical precedent. The structure of the board shapes the strategic direction and risk appetite of an organization, which are critical in decisions related to emerging technologies (Chen et al., 2021). The inclusion of these three indicators aimed to capture the most influential dimensions of board characteristics that affect technology-related decisions in SACCOs.

Board size was selected because it reflects the scale of oversight and decision-making capacity within an organization (Zeraati, 2024). Larger boards can offer a broader range of skills and perspectives, which may support more informed and strategic decision-making around innovation. However, very large boards may also slow down decisions due to coordination difficulties. This duality makes board size a relevant variable in understanding its role in technology adoption (Chen et al., 2021).

Board independence was included as it reflects the presence of directors who are not involved in the day-to-day management of the SACCO. Independent directors are generally more objective and provide checks and balances in governance processes (Paramesha et al., 2024). They are more likely to question management decisions, demand accountability, and promote innovations that improve long-term sustainability rather than short-term gains. Their influence can significantly shape whether a SACCO adopts emerging technologies (Zeraati, 2024).

Board diversity, particularly in terms of gender and professional background, has been associated with greater openness to innovation. Diverse boards bring varied experiences and viewpoints that can stimulate creative problem-solving and increase receptivity to new technologies. In the context of SACCOs, board diversity is especially important given the need to represent diverse member interests and adapt to a rapidly changing technological landscape (Paramesha et al., 2024).

1.1.4 Technology Characteristics

Technology characteristics are central to this study because an organization's perception of emerging technologies influences its willingness to adopt them (Eskandarany, 2024). Technology characteristics refer to the features and attributes of an emerging innovation that affect its adoption and implementation (Neumann et al., 2024). Organizations assess whether the benefits of an emerging technology outweigh the risks and challenges before integrating it into their operations (Noriega et al., 2023). This study measured technology characteristics using relative advantage, which evaluates whether AI, machine learning, and blockchain offer superior benefits compared to traditional credit analysis methods; trust, which assesses confidence in the accuracy and reliability of these technologies; compatibility, which determines how well the emerging technology aligns with the SACCO's existing systems and processes; security, which examines concerns related to data protection and fraud prevention; and complexity, which considers the ease or difficulty of implementing and using the technology (Neumann et al., 2024).

1.1.5 Deposit-Taking SACCOs in Kenya

SACCOs are member-owned financial institutions that offer financial services to members. These institutions focus primarily on mobilizing savings and providing credit (Batchu, 2023). SACCOs use a cooperative model characterized by members pooling their financial resources in order to create a fund that is then utilized to provide loan as well as other financial services (Njoroge &

Murinde, 2021). In SACCOs, every member owns a share and enjoys equal voting rights, which ensures democratic decision-making. SACCOs have the main goal of promoting financial inclusion through delivering affordable financial services and products that target underserved populations, such as low-income earners, small businesses, and rural communities. SACCOs usually obtain their revenue through loan fees and interest that may be re-invested or issued as dividends to members.

SACCOs offers a range of financial services, which include savings, loans and investment products. Saving options for members consist of regular savings accounts, fixed deposit accounts and target savings accounts (Njoroge & Murinde, 2021). The types of loans offered by SACCOs are emergency loans, asset financing loans for buying vehicle or property, and business loans for entrepreneurial ventures. In addition, SACCOs can offer investment products, such as buying shares in the cooperative, group investment projects and even insurance products (Batchu, 2023).

Emerging technologies, such as AI, blockchain and ML can be adopted by SACCOs to enhance their operations and services. SACCOs can use AI for credit analysis, fraud detection and even customer service (Tiwari et al., 2023). AI is capable of processing large datasets, identifying patterns and evaluating credit worthiness in a more accurate way in comparison to traditional methods. ML algorithms can be used to predict the likelihood of loan defaults, optimize lending practices, and even personalize financial products depending member behavior (Batchu, 2023). For instance, ML models can be used to analyze historical loan repayment trends in order to refine credit risk evaluation and automate the process of loan approval; thus, increasing their reliability and speed. Blockchain can be used to enhance efficiency, security and transparency of SACCO operations. This technology can be utilized for maintaining tamper-proof transaction records. Also, blockchain can be used to provide members with secure digital identities that enables them to seamlessly access financial services (Tiwari et al., 2023).

DTSs play a crucial role in Kenya's financial sector by providing essential financial services, particularly to underserved communities, offering savings and credit facilities to their members (Njoroge & Murinde, 2021). These institutions are integral in promoting financial inclusion, especially in rural areas, and supporting economic empowerment for many individuals and small businesses. DTSs in Kenya are regulated by the Sacco Societies Regulatory Authority (SASRA), which oversees their financial stability and ensures compliance with relevant regulations (Njoroge

& Murinde, 2021). There are 177 DTSs in Kenya – this will constitute the population for this study (SASRA, 2024). Despite their importance, there is limited research focusing on the implementation of emerging technologies such, AI, blockchain, and ML, within these SACCOs. Studying the adoption of these technologies is crucial, as it can enhance credit risk management, improve operational efficiency, and ultimately strengthen the role of SACCOs in the financial sector (Hassan, 2024).

1.2 Statement of the Problem

While emerging technologies such as AI, blockchain, and ML, are transforming credit analysis in financial institutions globally, their adoption among DTSs in Kenya remains limited (CIPIT, 2023). Globally, institutions in developed countries such as the U.S and the U.K have extensively adopted these technologies to improve credit risk management, with AI investments in the financial sector reaching $21 billion in 2023 (Statista, 2024). In Kenya, however, the adoption of these technologies is low in financial institutions despite the projected significant growth of the AI market coupled with their potential to enhance credit scoring, reduce defaults, and increase operational efficiency (Paradigm Initiative, 2022).

In Kenya, the adoption of emerging technologies in credit analysis, specifically artificial intelligence (AI), blockchain, and machine learning (ML), is at a nascent stage, particularly within the SACCO sector (Nyabwari & Kimutai, 2024). While commercial banks and fintech firms have begun integrating AI-driven tools such as chatbots and predictive credit scoring models, most deposit-taking SACCOs (DTSs) remain reliant on manual credit assessment methods. According to the 2023 SACCO Supervision Report by SASRA, over 50% of DTSs have not implemented basic digital platforms, such as mobile applications or internet banking systems, let alone advanced technologies like AI or blockchain (Nyabwari & Kimutai, 2024). This has led to a rising non-performing loan (NPLs) within the SACCO sector, which suggests weaknesses in borrower assessment and risk management. In 2016, the rate of NPLs was 5.23%, which increased to 6.14 percent in 2017, 6.3 percent in 2018, 6.15 percent in 2019, 8.39 percent in 2020 and 8.86 percent in 2021 (Nyabwari & Kimutai, 2024). Many SACCOs still rely on traditional, manual methods of credit evaluation, which are often subjective and inconsistent (Nyabwari & Kimutai, 2024)

Despite the recognized benefits of integrating advanced technologies into credit analysis, a significant number of Kenyan deposit-taking SACCOs have yet to adopt such innovations. According to the 2023 SACCO Supervision Annual Report by the SACCO Societies Regulatory Authority (SASRA), out of 684 regulated entities, 346 have not implemented USSD, mobile applications, or internet solutions to enhance service delivery. Furthermore, 35.63% of deposit-taking SACCOs still do not provide ATM services to their members, and only 14.29% have integrated their systems with PesaLink for settlement and clearance of funds (SASRA, 2024). These statistics highlight a considerable gap in technology adoption within the sector; thus, underscoring the need for a comprehensive analysis of the factors influencing the integration of emerging technologies in SACCO operations.

This problem primarily affects SACCOs, their members and the broader financial ecosystem in Kenya. The low adoption means that SACCOs do not leverage these technologies optimally to improve their credit risk assessment and expand access to credit, which adversely affects low-income and underserved people who rely on them for financial inclusion (Eskandarany, 2024; Hassan, 2024). Therefore, this study sought to understand the unique drivers and barriers for adoption of emerging technologies by SACCOs in developing economies since this can inform the development of targeted interventions, policies, and strategies to enhance the competitiveness and efficiency of SACCOs.

There are conceptual, methodological and contextual gaps in the existing literature. Conceptually, extant research has focused on various determinants, such as attitude towards AI, perceived trust, perceived risk, subjective norms, and perceived usefulness (Rahman et al., 2023); technological infrastructure, ethical concerns, and lack of cohesive AI strategies (Eskandarany, 2024; Hassan, 2024); regulatory burden, human capital, and ethical considerations (Nwachukwu & Olatunji, 2023; Wang, 2024). These conceptualizations show little empirical focus on organizational characteristics and management perspectives regarding the role of these technologies in enhancing credit analytics. Contextually, existing studies have also been conducted in diverse contexts, including the banking sector in Malaysia (Rahman et al., 2023), Saudi Arabian banks (Eskandarany, 2024), financial institutions in the United States (Nwachukwu & Olatunji, 2023) and financial services sector in South Africa (Hassan, 2024). As a result, the findings from these studies cannot be applied in the context of DTSs in Kenya. Additionally, a wide range of methodologies have been employed in studies focusing on the adoption of emerging technologies, which include mixed methods (Rahman et al., 2023), qualitative (Eskandarany, 2024), systematic review (Wamg, 2024). The use of diverse methodologies in existing studies yield different findings and hinders the comparison of studies. The proposed research sought to address these gaps by examining the factors that influence the adoption of emerging technologies in DTSs in Kenya using a descriptive cross-sectional design.

1.3 Main Objective of the Study

The main objective of this research was to examine the factors influencing the adoption of emerging technologies, including artificial intelligence, block chain, and machine learning, in credit analysis among DTSs in Kenya.

1.3.1 Specific Objectives of the Study

1. To determine the influence of financial capacity on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.
2. To determine the effect of board characteristics on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.
3. To determine the effect of technology characteristics on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.

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1.4 Research Questions

1. How does financial capacity influence the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.
2. What is the effect of board characteristics on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.
3. What is the effect of technology characteristics on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.

1.5 Significance of the Study

The findings of this study may be significant to policymakers, practitioners, and academicians and researchers.

1.5.1 Policymakers

This study might be particularly valuable for policymakers and regulators who are aiming to promote digital financial inclusion and technological innovation in the cooperative sector. The research offered recommendations on the regulatory frameworks needed to support the adoption of emerging technologies, addressing concerns relating to the capacity of SACCOs to adopt such technologies.

1.5.2 Practitioners

SACCO managers, decision-makers, and board members might find this study useful in understanding the factors that enable or hinder the adoption of emerging technologies within their institutions. The study provided actionable insights into how to align organizational characteristics with successful implementation strategies for emerging technologies; thus, improving operational efficiency, risk management, and service delivery. Technology providers, such as those offering AI-based solutions for financial institutions, may benefit from the study's findings on the barriers and opportunities specific to SACCOs. This may help them tailor their offerings to meet the unique needs of smaller financial institutions, making their products more accessible and relevant to SACCOs.

1.5.3 Academicians and Researchers

This study might also be particularly valuable for policymakers and regulators who are aiming to promote digital financial inclusion and technological innovation in the cooperative sector. The research offered recommendations on the regulatory frameworks needed to support the adoption of emerging technologies, addressing concerns relating to the capacity of SACCOs to adopt such technologies.

1.6 Scope of the Research

The conceptual scope of this study was limited to examining the factors influencing the adoption of emerging technologies, including artificial intelligence, block chain, and machine learning, in credit analysis among DTSs in Kenya. While there are numerous factors that influence the adoption of emerging technologies, this study focused on organizational factors and management perspectives. The study was guided by the Technology-Organization-Environment (TOE) theory. The methodological scope of the study was quantitative, which will be executed using the descriptive correlational design and primary and secondary data collected. The population of the study will be the 177 DTSs operating in Kenya. Participants consisted of managers of these SACCOs. The study was conducted in April 2025.

1.7 Chapter Summary

The background, context, statement of the problem and objectives of this study have been presented in this chapter. The scope and significance of this research have also been discussed.

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CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews theoretical and empirical literature on the adoption of emerging technologies in credit analysis by financial institutions. In addition, the research gaps in existing literature, conceptual framework and operationalization of study variables are discussed in this chapter.

2.2 Theoretical Foundation

2.2.1 Technology-Organization-Environment (TOE) Theory

The Technology-Organization-Environment (TOE) framework, developed by Tornatzky, Fleischer and Chakrabarti (1990), provides a framework for understanding how technological, organizational, and environmental contexts influence the adoption of technological innovations. This theory posits that the adoption of emerging technologies is shaped by three interrelated factors: technological characteristics, organizational attributes, and external environmental conditions (Tornatzky et al., 1990).

The TOE framework's propositions are rooted in the notion that technology adoption is not solely determined by the features of the technology itself but is also influenced by internal organizational dynamics as well as external environmental pressures (Tornatzky et al., 1990). For instance, technological factors such as perceived benefits, compatibility, and complexity directly affect adoption decisions (Malik et al., 2021). at the same time, organizational factors, such as culture, structure, and resources, determine an organization's readiness to adopt and implement emerging technologies (Awa et al., 2017). Additionally, environmental factors, such as regulatory frameworks, market competition, and stakeholder pressures, further influence the adoption process (Rambe et al., 2022).

One of its key strengths of the TOE framework lies in its ability to integrate multiple dimensions of influence, providing a nuanced understanding of technology adoption (Awa et al., 2017). The propositions of this theory have also been validated in empirical research (Gupta et al., 2022; Malik et al., 2021). This theory is also holistic and has been applied across various sectors. However, the broad scope of this theory has been criticized on the basis that it can sometimes lead to oversimplification since it does not explicitly account for the interaction between individual factors within each dimension (Rambe et al., 2022). Additionally, TOE's reliance on contextual factors means that its applicability may vary across different industries and regions, which may require adaptations to suit specific study contexts (Awa et al., 2017). Nevertheless, its flexibility and comprehensive nature make it a valuable tool for analyzing technology adoption in diverse settings.

The TOE framework is adequate as a standalone theoretical foundation because it encompasses all three key determinants (financial capacity, board characteristics, and technological characteristics) within its technological, organizational, and environmental dimensions (Rambe et al., 2022). It provided a holistic approach to understanding how SACCOs adopt emerging technologies for credit analysis, making it the most suitable theory for this study. Given its broad applicability to organizational technology adoption, there is no need to introduce an additional theoretical framework.

The organizational dimension of the TOE framework encompasses internal factors that affect technology adoption, including financial capacity. SACCOs with higher profitability and strong capital adequacy are more likely to adopt AI-driven credit analysis tools, as they can afford the necessary investments. The TOE model supports this by acknowledging that organizations with stronger financial resources are better positioned to integrate emerging technologies and sustain them in the long run.

The TOE framework also incorporates organizational structure and leadership, which directly relates to the role of board size, board independence, and board diversity in technology adoption. According to the framework, organizations with strong governance structures can drive technology adoption more effectively by providing strategic direction, ensuring accountability, and securing necessary funding for implementation (Rambe et al., 2022). A diverse and independent board can encourage innovation by advocating for data-driven decision-making and risk management improvements.

The TOE framework highlights how technological factors influence adoption decisions, which aligns with this study's focus on relative advantage, trust, compatibility, security, and complexity as key determinants. The framework posits that organizations assess emerging technologies based on perceived benefits, risks, and alignment with existing operations (Malik et al., 2021; Awa et al., 2017). SACCOs must evaluate whether AI, machine learning, and blockchain offer a relative advantage over traditional credit analysis methods while considering issues such as security and trust before adopting them.

2.3 Empirical Literature

The selection of the three main categories of factors, financial capacity, board characteristics, and technology characteristics, was guided by a combination of theoretical alignment with the TOE framework and evidence from prior empirical studies. These categories correspond respectively to the organizational and technological dimensions of the TOE model, which emphasizes that both internal capabilities and perceptions of technology shape adoption outcomes. Financial capacity and board characteristics represent key organizational attributes that determine a SACCO's ability and readiness to adopt innovation, while technology characteristics reflect how the innovation is perceived by the decision-makers (Hassan, 2024; Javaid et al., 2022). This section presents a review of the literature on the adoption of emerging technologies in credit analysis.

2.3.1 Financial capacity and the Extent of Adoption of Emerging Technologies

Financial capacity are critical determinants of an organization's ability to adopt and sustain emerging technologies. In the context of SACCOs, financial strength directly influences investment decisions, including the integration of advanced credit analysis tools such as artificial intelligence, machine learning, and blockchain (Paramesha et al., 2024). Financially stable SACCOs are better positioned to allocate resources for technology adoption, while those with limited financial capacity may struggle to implement and maintain new systems (Noriega et al., 2023). The financial health of a SACCO also affects its ability to manage risks, expand its operations, and comply with regulatory requirements. This study considers four key financial indicators of profitability, asset quality, and capital adequacy, in order to assess how financial strength influences the adoption of emerging technologies in credit analysis.

Profitability measures a SACCO's ability to generate earnings relative to its expenses and operational costs. Higher profitability allows SACCOs to reinvest in technology upgrades, improve credit risk assessment, and enhance service delivery (Noriega et al., 2023). Asset quality assesses the proportion of non-performing loans (NPLs) within a SACCO's loan portfolio, with poor asset quality signaling high credit risk and financial instability that may hinder technology adoption. Lastly, capital adequacy measures a SACCO's financial strength and ability to absorb potential losses (Gupta et al., 2022). Well-capitalized SACCOs have greater resilience and are more likely to embrace innovation in credit analysis (Gupta et al., 2022). These financial indicators provide a comprehensive framework for evaluating the role of financial capacity in shaping technology adoption decisions within SACCOs.

Costs as barriers to the adoption of emerging technologies has been identified in the literature. Rane et al. (2023) examined the integration of blockchain and AI in credit risk management processes among financial institutions in India. The study explored how these technologies are being used to enhance transparency and efficiency in credit analysis. Using a systematic review approach, the researchers collected data studies conducted in India with financial institutions using these technologies. The findings revealed that blockchain technology was primarily adopted for transaction verification and fraud prevention, while AI was used to develop automated credit scoring models (Rane et al., 2023). However, the study also highlighted challenges such as high implementation costs and a lack of skilled personnel, which hindered widespread adoption due to financial requirements. Despite these barriers, institutions that successfully integrated these technologies reported significant improvements in credit risk assessment accuracy and operational efficiency. This study focused on cost as a barrier but did not examine the financial characteristics of institutions.

In Bangladesh, Majumder (2023) examined the role of AI in credit risk management in a commercial bank. The study aimed to investigate how AI tools are used to improve credit scoring and risk assessment processes. Using a case study approach that combined surveys and interviews with managers of the bank, the researchers found that AI was integrated into credit scoring models to analyze borrower data more efficiently (Majumder, 2023). The findings revealed that commercial bank being studied was able to reduce non-performing loans by 15% due to more accurate risk predictions. However, the study also highlighted barriers to adoption, such as high implementation costs and a lack of skilled personnel to operate AI systems (Majumder, 2023). These findings underline the potential of AI in transforming credit analysis while emphasizing the need for capacity-building initiatives to enhance adoption. A weakness of this study is that it focused on cost as a barrier but did not examine the financial characteristics of institutions

A study by Hoque et al. (2024) examined the integration of AI and blockchain in credit risk management processes by microfinance institutions. The research studied the extent of adoption, its impact on operational efficiency, as well as the challenges and opportunities associated with these technologies. Using a qualitative approach, the study involved interviews with senior managers from ten microfinance institutions. The findings revealed that AI-powered credit scoring models significantly reduced the time required to process loan applications, while blockchain enhanced the security and traceability of credit transactions (Hoque et al., 2024). At the same time, the study also identified challenges such as limited financial resources and a lack of regulatory frameworks supporting technology adoption. The authors emphasized the need for targeted interventions, including dedicated budgets for technology infrastructure, to facilitate adoption (Hoque et al., 2024). This study focused on cost as a barrier but did not examine the financial characteristics of institutions.

Bouteraa et al. (2024) studied the application of AI in credit analysis by commercial banks in Malaysia. The purpose of the research was to evaluate the effectiveness of AI-driven solutions in improving credit risk management. Using a mixed-methods approach, the study combined surveys with interviews of bank managers. The findings showed that AI-enabled systems, such as automated credit scoring models, were increasingly being used to enhance decision-making in loan approvals. However, the adoption rate was still low due to challenges such as significant capital investments needed, inadequate data ecosystems and a lack of skilled personnel (Bouteraa et al., 2024). This study focused also on cost as a barrier but did not examine the financial characteristics of institutions.

Javaid et al. (2022) explored the application of blockchain technology in credit analysis. The study focused on how blockchain facilitates transaction verification and fraud prevention in lending processes. Using a systematic review methodology with studies conducted from across the globe, the researchers indicated that blockchain reduced credit fraud incidents by 30% through enhanced transparency and accountability in lending transactions. Additionally, Javaid et al. (2022) revealed that the frequency of blockchain usage in daily operations varied depending on the institution's size and technological capabilities. The authors concluded that blockchain holds significant promise for improving credit analysis; however, its adoption is hindered by the need for substantial investment in infrastructure and regulatory uncertainties.

2.3.2 Board characteristics and the Extent of Adoption of Emerging Technologies

Board characteristics play a fundamental role in shaping an organization's strategic direction, including its ability to adopt and implement emerging technologies. Strong boards ensure accountability, transparency, and effective decision-making, which are crucial for SACCOs considering investments in financial technology (Paramesha et al., 2024). Board characteristics influence risk management practices, innovation adoption, and the overall operational efficiency of financial institutions (Zeraati, 2024). In the context of this study, board characteristics were assessed using board size, board independence, and board diversity, as these factors determine the leadership capacity to drive digital transformation (Zeraati, 2024).

Board size refers to the number of directors overseeing an organization's operations. A larger board may bring diverse expertise and broader perspectives, enhancing decision-making on complex matters like technology adoption. However, excessively large boards may lead to slower decision-making processes. Board independence measures the proportion of non-executive or independent directors who are not directly involved in daily SACCO management (Chen et al., 2021). Independent directors contribute objective insights and reduce the risk of internal biases, improving governance effectiveness. Board diversity captures variations in board members' backgrounds, including gender, professional experience, and educational qualifications (Zeraati, 2024). Diverse boards are more likely to consider innovative solutions and advocate for inclusive policies that drive technology adoption (Paramesha et al., 2024). By examining these board characteristics indicators, this study seeks to understand how leadership structures influence SACCOs' willingness and capacity to integrate AI, machine learning, and blockchain technologies in credit analysis.

Chen et al. (2021) explored the impact of having a strategic vision on the adoption of blockchain technology in credit analysis among banks in Taiwan. The study investigated how a clear strategic vision for emerging technology adoption influences the integration of blockchain into credit risk management processes. Using a mixed methods approach, the researchers collected data from banks through surveys and interviews. The findings indicated that banks with a well-defined strategic vision for technology adoption were more successful in integrating blockchain into their operations (Chen et al., 2021). These banks had established clear goals and timelines for adoption, which helped align efforts across departments and ensured the efficient allocation of resources. From the findings, the authors emphasized the importance of strategic planning as a critical factor in driving technology adoption. While this study underscores the importance of governance, it did not outline the specific board characteristics and how they influence adoption.

In Saudi Arabia, Eskandarany (2024) examined the adoption of AI and ML in the banking sector with a focus on the role that the board of directors play and the effect of these technologies in preventing cyberattacks. The researchers employed a qualitative approach involving interviews with board members from the leading banks in the country. The themes from this study suggested that AI and ML can enhance threat detection, prevent fraud, automate processes, help achieve regulatory compliance, and mitigate cyberattacks. Nevertheless, some challenges were reported, which included limited technological capabilities, lack of AI strategies, and ethical concerns associated with data privacy. Also, the findings indicated that the board of directors has a key role with respect to offering strategic leadership, securing resources, and fostering partnerships needed to integrate AI (Eskandarany, 2024). This study showed the important role that board of directors play; however, the specific characteristics of the board were not studied.

Kok and Siripipatthanakul (2023) examined the impact of governance structure on the adoption of AI and ML technologies in credit analysis amongst financial institutions in Malaysia. The study looked at how the robustness of governance structures impacts the decision-making process for technology adoption. Using a qualitative research design, the researchers performed a narrative synthesis and content analysis. The findings revealed that institutions with strong governance structures were more effective in adopting AI and ML tools, which can be attributed to clear decision-making processes and accountability mechanisms in place. These institutions also reported higher levels of stakeholder trust and confidence, which further facilitated the adoption process (Kok & Siripipatthanakul, 2023). The study highlighted the importance of robust governance structures in ensuring successful technology adoption but left a gap with respect to the importance of board characteristics.

2.3.3 Technology Characteristics and the Extent of Adoption of Emerging Technologies

Technology characteristics influence an organization's decision to adopt and implement emerging innovations by shaping perceptions of their benefits, risks, and feasibility (Bhatti, 2019). The Technology-Organization-Environment (TOE) framework emphasizes that organizations assess emerging technologies based on their functional advantages, compatibility with existing systems, and potential challenges (Cubric, 2020). In SACCOs, technology adoption is driven by its ability to enhance efficiency, reduce credit risk, and improve decision-making processes. This study examines technology characteristics through five key indicators: relative advantage, trust, compatibility, security, and complexity. These indicators have been shown to affect the adoption of AI, machine learning, and blockchain in credit analysis (Cubric, 2020).

Relative advantage refers to the perceived benefits of emerging technologies over traditional credit analysis methods. SACCOs are more likely to adopt emerging technologies if they offer superior accuracy, speed, and cost-effectiveness. Trust represents confidence in the reliability and effectiveness of AI-driven credit scoring and blockchain security. Institutions that trust technology to deliver accurate assessments and fraud protection are more inclined to integrate it into their operations. Compatibility assesses how well an emerging technology aligns with existing SACCO processes, infrastructure, and regulatory requirements (Bhatti, 2019). A high level of compatibility facilitates smoother adoption. Security concerns the ability of AI and blockchain to protect sensitive financial data from fraud, cyber threats, and unauthorized access (Polisetty et al., 2024). Finally, complexity refers to the perceived difficulty in implementing and using emerging technologies. Technologies that require extensive technical expertise, high implementation costs, or significant staff training may face adoption resistance (Neumann et al., 2024). By analyzing these indicators, this study aims to determine how technological factors impact SACCOs' willingness and ability to integrate digital solutions in credit analysis.

Jena (2022) investigated the role of management perceptions of security in the adoption of blockchain technology in Indian banks. The study aimed to determine how concerns about data security and privacy influence the decision to adopt blockchain for credit analysis. Using a descriptive survey design, the findings revealed that managers who perceived blockchain as a secure and reliable technology were more likely to support its adoption in their banks. However, concerns about regulatory compliance and potential vulnerabilities were found to negatively affect the intention to adopt this technology. The study concluded that addressing security concerns through robust encryption and compliance with regulatory standards is essential for fostering positive management perspectives and facilitating technology adoption. This study only focused on security; leaving a gap with respect to relative advantage, trust, complexity and compatibility.

Rahman et al. (2023) conducted a study aimed at examining the adoption of AI in Malaysia's banking industry. The focus of the study was on the importance, challenges as well as factors influencing the adoption of these technologies. Rahman (2023) employed a mixed methods approach with banking officials. The results showed that attitudes towards AI, its perceived usefulness, perceived trust, perceived risk and subjective norms had an influence on the adoption of AI by banks in Malaysia. Rahman et al. (2023) stressed the need for addressing the perceptions of bank managers regarding AI in order to enhance its adoption. A limitation of this study is that it did not cover other technology characteristics, including relative advantage, compatibility, security and complexity.

Polisetty et al. (2024) conducted a mixed methods study on the role of management perceptions in the adoption of emerging technologies among business-to-business small and medium enterprises (SMEs) in India. The study aimed to examine how perceptions of relative advantage, compatibility, and complexity influence the decision to adopt AI and ML tools. Using a mixed-methods approach, the researchers collected data through surveys and interviews. The findings revealed that managers who perceived AI and ML tools as offering significant advantages over traditional methods were more likely to advocate for their adoption (Polisetty et al., 2024). Similarly, perceptions of compatibility with existing systems and low complexity were positively associated with adoption rates. Based on the findings, it was concluded that management perceptions are a critical factor in shaping technology adoption decisions, as they influence the willingness of organizations to embrace innovation. A weakness of this study is that it did examine security and trust.

A review article by Kuznetsov et al. (2024) explored the impact of management trust in emerging technologies on their adoption in the banking sector in Europe. The study aimed to assess how trust in the reliability and effectiveness of AI and blockchain technologies influences their integration into credit risk management processes. The findings indicated that managers who trusted the accuracy and security of these technologies were more likely to support their adoption. Conversely, concerns about data privacy and potential errors were identified as barriers to adoption. The study emphasized the importance of building trust in emerging technologies through demonstrations, pilot projects, and transparent communication to facilitate their adoption. A limitation of this study is that it did not cover other technology characteristics, including relative advantage, compatibility, security and complexity.

Mogaji and Nguyen (2021) studied the influence of management perceptions of complexity on the adoption of AI and ML technologies in credit analysis within financial institutions in both developed and developing countries, including Vietnam, Nigeria, Canada and the United Kingdom. The study assessed how perceptions of the ease of implementation and use of these technologies impact adoption decisions. Using a qualitative research design, the researchers conducted interviews with senior managers from financial institutions in these countries. The findings indicated that managers who perceived AI and ML tools as complex and difficult to implement were less likely to support their adoption in their banks. The results also noted that institutions that provided training and support to reduce perceived complexity reported higher adoption rates. From the findings, Mogaji and Nguyen (2021) stressed the importance of simplifying the implementation process and providing adequate training to foster positive management perspectives.

2.4 Research Gap

Conceptual, contextual and methodological gaps have been identified in the existing literature. With respect to conceptual gaps, different conceptualizations of the adoption of the emerging technologies exist with studies looking at different aspects of adoption, which include the use of AI and blockchain for enhancing transparency and efficiency in credit analysis (Rane et al., 2023); use of these technologies to improve the accuracy of risk predictions (Majumder, 2023); use of these technologies to foster financial inclusion through accurate credit evaluation; and prevention of cyberattacks (Eskandarany, 2024). Different conceptualizations of key constructs in existing research can constitute a significant research gap because they often lead to inconsistencies in understanding, measurement, and application of those constructs. This lack of consensus can create ambiguity, hinder comparability across studies, and limit the ability to draw definitive conclusions. To address this gap, the extent of adoption of emerging technologies in this study will be defined as the degree to which SACCOs accept, integrate, and utilize AI, blockchain, and ML technologies in their credit analysis processes.

Additionally, contextual gaps were identified. In particular, existing studies have been conducted in India (Rane et al., 2023), Bangladesh (Majumder, 2023), Peru (Maehara et al., 2024), Nepal (Bhatta et al., 2023), Malaysia (Bouteraa et al., 2024), Iran (Zeraati, 2024), and Taiwan (Chen et al., 2021). Consequently, the findings from existing studies might not be applicable in Kenya due to unique culture, economic, technological and regulatory environments. To address this gap, the setting for this study was DTSs in Kenya, which are under-researched.

Methodological gaps were also been spotted in the existing literature. In this regard, varied methodologies have been adopted to study the adoption of these emerging technologies, including mixed methods (Chen et al., 2021; Rahman et al., 2023), qualitative approaches (Eskandarany, 2024; Kok & Siripipatthanakul, 2024), and descriptive design (Zeraati, 2024). Methodological variations in existing studies constitute a significant research gap because they can lead to incomparable findings, which makes it difficult to build a cohesive body of knowledge. To address this gap, the current study adopted the descriptive cross-sectional design to provide a snapshot of the status of the adoption of emerging technologies by DTSs. Table 2.1 presents a summary of the research gaps.

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Table 2. 1: Summary of Research Gaps

Study	Focus of the Study	Findings	Research Gap	Focus of the current study
Rane et al. (2023)	Examine the integration of blockchain and AI in credit risk management processes within financial institutions in India	The findings revealed that blockchain technology was primarily adopted for transaction verification and fraud prevention, while AI was used to develop automated credit scoring models	Contextual gap – this study was conducted in India; hence, the findings may not be applicable in Kenya Conceptual gap – the adoption of AI and blockchain was defined in terms of using these technologies to enhance transparency and efficiency in credit analysis. Methodological gap – this study used the systematic review approach	The context of the current study was the DTS in Kenya. The adoption of emerging technologies in this study was defined as the process by which these institutions accept, integrate, and utilize AI, blockchain, and ML technologies to enhance their credit risk management practices. The current study adopted the descriptive cross-sectional design to provide a snapshot of the status of the adoption of emerging technologies by DTSs.
Majumder (2023)	The role of AI in credit risk management in a commercial bank in Bangladesh	The findings revealed that commercial bank being studied was able to reduce non-performing loans by 15% due to more accurate risk predictions	Contextual gap – this study was conducted in Bangladesh; hence, the findings may not be applicable in Kenya	The context of the current study was the DTS in Kenya. The adoption of emerging technologies in this study was defined as the process by which these institutions accept, integrate, and utilize AI, blockchain, and ML technologies to enhance their credit risk management practices.

			Conceptual gap – the adoption of AI and blockchain was defined in terms of using these technologies to enhance accurate risk predictions. Methodological gap – this study used the systematic review approach	The current study adopted the descriptive cross-sectional design to provide a snapshot of the status of the adoption of emerging technologies by DTSs.
Maehara et al., (2024)	The role of ML in enhancing financial inclusion through more accurate credit evaluation.	The findings showed that institutions employing ML models significantly improved their predictive accuracy; hence, enabling them to make better-informed lending decisions that led to increased financial inclusion	Contextual gap – this study was conducted in Peru; hence, the findings may not be applicable in Kenya Conceptual gap – this study focused on financial inclusion. Methodological gap – this study used secondary data spanning five years	The context of the current study was the DTS in Kenya. The adoption of emerging technologies in this study was defined as the process by which these institutions accept, integrate, and utilize AI, blockchain, and ML technologies to enhance their credit risk management practices. The current study adopted the descriptive cross-sectional design to provide a snapshot of the status of the adoption of emerging technologies by DTSs.
Zeraati (2024)	To examine the role of organizational culture in the adoption of AI and ML	Organizations with a culture that values innovation and	Contextual gap – this study was conducted in Iran;	The context of the current study will be the DTSs in Kenya.

	technologies within financial institutions in Iran	encourages experimentation were more likely to adopt AI and ML tools in credit analysis	this means the findings are not applicable in the Kenyan context. Conceptual gap: the study focused only on organizational culture.	The determinants in the current study will include other factors, such as management perspectives.
Rahman et al. (2023)	To examine the importance, challenges as well as factors influencing the adoption of AI in Malaysian banks	Attitudes towards AI, its perceived usefulness, perceived trust, perceived risk and subjective norms had an influence on the adoption of AI by banks in Malaysia	Contextual gap – this study was conducted in Malaysia; hence, the findings may not be applicable in Kenya Conceptual gap – this study focused in financial inclusion. Methodological gap – this study used a mixed methods approach	Besides perceptions, the current study also looked at other determinants including organizational characteristics. The current study adopted the descriptive cross-sectional design with primary data to provide a snapshot of the status of the adoption of emerging technologies by DTSs in Kenya.
Eskandarany, (2024)	To examine the adoption of AI and ML in the banking sector with a focus on the role that the board of directors play and the effect of these technologies in preventing cyberattacks	The board of directors has a key role with respect to offering strategic leadership, securing resources, and fostering partnerships needed to integrated AI	Contextual gap – this study was conducted in Saudi Arabia, which implies that its results might not be applicable in Kenya.	The context of the current study was DTSs in Kenya. The descriptive cross-sectional design was adopted in the present study.

			Methodological gap – this study adopted a qualitative approach	
Kok and Siripipatthanakul (2023)	Examined the influence of governance structure on the adoption of AI and ML technologies in credit analysis within financial institutions in Malaysia	The findings revealed that institutions with strong governance structures were more effective in adopting AI and ML tools, which can be attributed to clear decision-making processes and accountability mechanisms in place.	Contextual gap – this study was conducted in Malaysia, which implies that its results might not be applicable in Kenya. Methodological gap – this study adopted a qualitative approach	The context of the current study was DTSs in Kenya. The descriptive cross-sectional design was adopted in the present study. Besides organizational structure, this study also looked at other determinants including the role of management perspectives.
Polisetty et al. (2024)	The role of management perceptions in the adoption of emerging technologies with business-to-business small and medium enterprises (SMEs) in India	Managers who perceived AI and ML tools as offering significant advantages over traditional methods were more likely to advocate for their adoption	Contextual gap – the study was conducted in India; thus, the findings cannot be applied in Kenya. Methodological gap – the study adopted a mixed methods approach	The context of the current study was DTSs in Kenya. The descriptive cross-sectional design was adopted in the present study. Besides organizational structure, this study also looked at other determinants including the role of management perspectives.
Jena (2022)	The effect of management perceptions of security in the adoption of blockchain technology in Indian banks	Managers who perceived blockchain as a secure and reliable	Contextual gap – the study was conducted in India; thus, the	The context of the current study was DTSs in Kenya. The descriptive cross-sectional design was adopted in the present study.

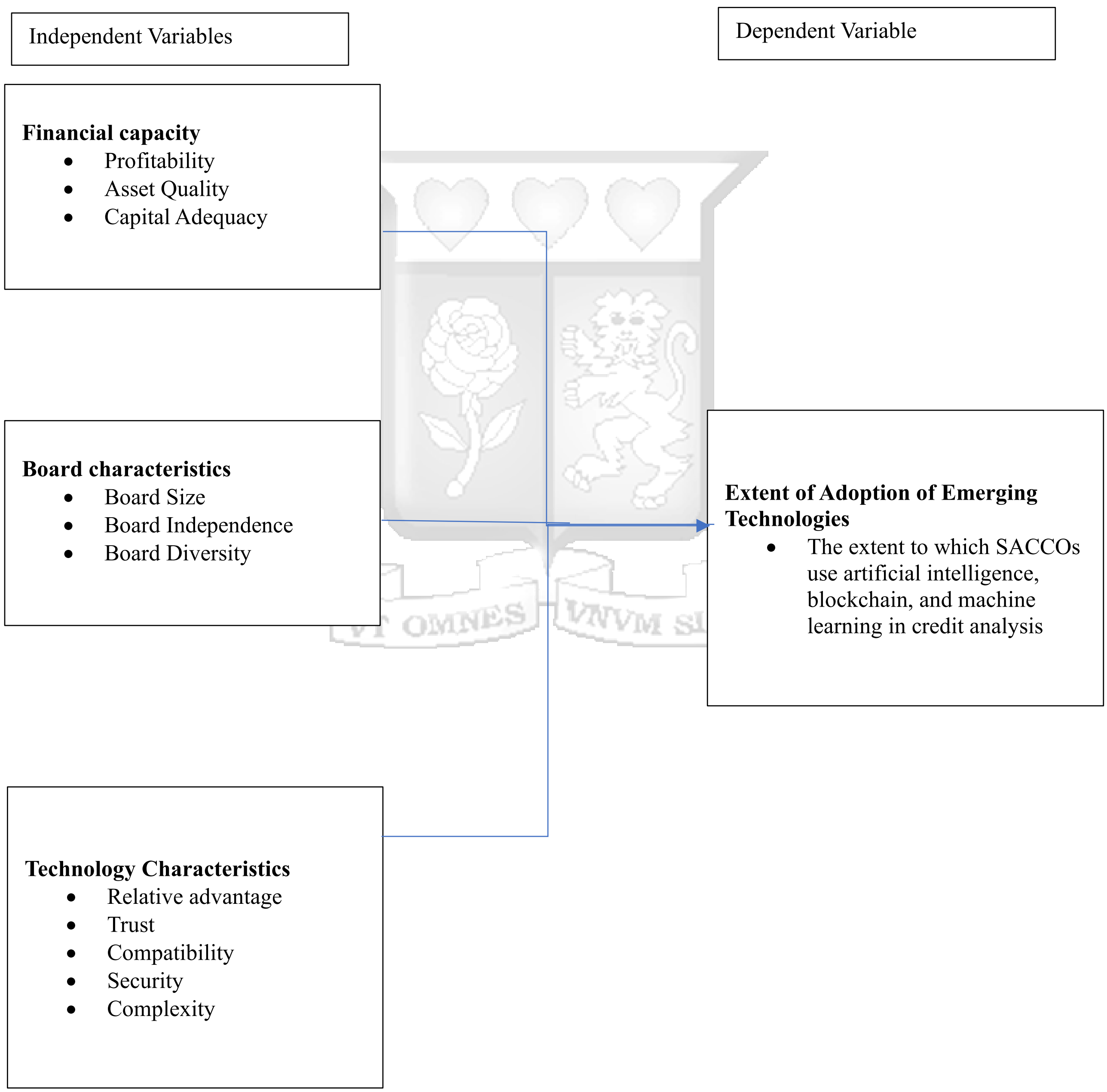
		technology were more likely to support its adoption in their banks	findings cannot be applied in Kenya. Methodological gap – the study adopted a mixed methods approach Conceptual gap – this study focused only on management perceptions regarding the security of blockchain technology	Besides management perceptions, this study also looked at other determinants including the role played by organizational characteristics.
Mogaji and Nguyen (2021)	The influence of management perceptions of complexity on the adoption of AI and ML technologies in credit analysis within financial institutions in both developed and developing countries, including Vietnam, Nigeria, Canada and the United Kingdom	Managers who perceived AI and ML tools as complex and difficult to implement were less likely to support their adoption in their banks	Contextual gaps – the context of this study was Vietnam, Nigeria, Canada and the United Kingdom; this means that the findings might not apply in the Kenyan context Methodological gap – this study employed a qualitative approach	The context of the current study was DTSs in Kenya. The descriptive cross-sectional design was adopted in the present study.

Source: Researcher (2025)

2.5 Conceptual Framework

Figure 2.1 shows the conceptual framework for this research. It shows the relationships between the dependent variable (adoption of emerging technologies in credit analysis) and independent variables (financial capacity, board characteristics and technology characteristics) as well as their indicators.

Figure 2. 1: Conceptual Framework



Source: Researcher (2025)

2.6 Operationalization of Study Variables

Table 2.2 shows how the variables in this study were operationalized.

Table 2. 2: Operationalization of Study Variables

Variable	Indicators	Measurement	Data Analysis	Supporting theory	Supporting Literature
Financial capacity	Profitability	Ratio of total revenue minus operating expenses divided by the total revenue	Quantitative	TOE	(Gupta et al., 2022)
	Asset Quality	Non-performing loans ratio	Quantitative	TOE	(Noriega et al., 2023)
	Capital Adequacy	Capital adequacy ratio	Quantitative	TOE	
Board characteristics	Board size	Number of board members	Quantitative	TOE	(Mogaji & Nguyen, 2021)
	Board independence	Proportion of independent directors on a board	Quantitative	TOE	(Noriega et al., 2023)
	Board diversity	Female ratio (Ratio of female directors to total directors)	Quantitative	TOE	(Noriega et al., 2023)
Technology Characteristics	Relative advantage	5-point Likert scale (ordinal	Quantitative	TOE	(Mogaji & Nguyen, 2021)
	Trust	5-point Likert scale (ordinal	Quantitative	TOE	(Nobanee et al., 2024)
	Compatibility	5-point Likert scale (ordinal	Quantitative	TOE	(Nobanee et al., 2024)
	Security	5-point Likert scale (ordinal	Quantitative	TOE	(Javaid et al., 2022)
	Complexity	5-point Likert scale (ordinal	Quantitative	TOE	(Neumann et al., 2024)
Extent of adoption of emerging technologies	The extent to which SACCOs use artificial intelligence, blockchain, and machine learning in	5-point Likert scale (ordinal)	Quantitative	TOE	(Neumann et al., 2024)

Variable	Indicators	Measurement	Data Analysis	Supporting theory	Supporting Literature
	credit analysis				

Source: Researcher (2025)

2.7 Chapter Summary

This chapter discussed the theoretical and empirical literature on the adoption of emerging technologies in credit analysis by financial institutions. Moreover, the research gaps in existing literature, conceptual framework and operationalization of study variables are discussed in this chapter.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses the methodology that were adopted for the proposed study. The aspects discussed are the research philosophy, design, population, sampling design, data collection methods, research quality including validity and reliability, data analysis, and ethical considerations.

3.2 Research Philosophy

Research philosophy refers to the set of beliefs that guide how researchers approach their studies (Bell et al., 2022). The four main philosophies are interpretivism, positivism, realism, and pragmatism. Interpretivism focuses on understanding subjective experiences and social contexts, often using qualitative methods like interviews or case studies (Bougie & Sekaran, 2019). Positivism, on the other hand, assumes that reality is objective and measurable, relying on quantitative methods such as surveys and experiments to test hypotheses and establish generalizable patterns (Easterby-Smith et al., 2021). Realism combines elements of both positivism and interpretivism, acknowledging that while some aspects of reality are observable, others are hidden and require deeper investigation (Bell et al., 2022). Finally, pragmatism prioritizes practical solutions over philosophical debates using mixed methods to address research problems effectively (Morgan, 2014).

This study adopted a positivist philosophy because it aligns with the research objectives, which focus on measuring and analyzing the adoption of emerging technologies in credit analysis. Positivism is suitable for this study as it emphasizes objective measurement, hypothesis testing, and the use of quantitative data to establish patterns and relationships (Bougie & Sekaran, 2019). The study aimed to quantify the extent of technology adoption, evaluate organizational factors, and assess management perspectives using structured surveys and statistical analysis. These methods require an objective and systematic approach, which positivism provides. Furthermore, positivism allows for generalizable findings, which are essential for informing policy and practice in the financial sector (Easterby-Smith et al., 2021).

3.3 Research Design

A research design denotes a framework or blueprint that guides the entire research process. It outlined how data needs to be collected, analyzed, and interpreted to answer the research questions (Raju & Prabhu, 2019). This study adopted the descriptive correlational design, which involves collecting data at a single point in time to describe the characteristics, behaviors, or conditions of a population (Easterby-Smith et al., 2021). The correlational nature of the design enables the researcher to analyze relationships between variables without manipulating any conditions. This made it an ideal choice for understanding the determinants and trends in a real-world setting.

3.4 Population of the Study

A study population refers to the complete group of individuals, organizations, or entities that share common characteristics and from which a sample is drawn for research purposes (Creswell & Creswell, 2018). It represents the broader group to which the study's findings will be generalized. For this study, the population consisted of all the 177 managers drawn from the licensed DTSs in Kenya as documented by the Sacco Societies Regulatory Authority (SASRA, 2025).

3.5 Census Approach

This study adopted a census approach, which involved collecting data from every member of the population rather than selecting a subset or sample (Schindler, 2022). It is typically used when the population size is small and manageable; thus, ensuring comprehensive and accurate representation (Easterby-Smith et al., 2021). In this study, all 177 licensed DTSs in Kenya as outlined by SASRA (2024) were targeted. This approach is justified by the relatively small size of the population, which allows for the inclusion of all SACCOs without the logistical challenges often associated with larger populations. Therefore, this study surveyed 177 respondents from these SACCOs.

The respondents for this study consisted of the managers of the DTSs in Kenya, including key roles such as credit managers, information technology managers, and operations managers. These individuals are directly involved in decision-making processes related to credit risk management and technology adoption within their organizations. Managers are well-positioned to provide informed insights into the extent of adoption of emerging technologies, such as artificial intelligence, blockchain, and machine learning, as they oversee the implementation, integration, and utilization of these tools in daily operations

3.6 Data Collection Methods

This study employed both primary and secondary data collection methods to ensure comprehensive and robust findings. Primary data was collected using structured questionnaires, which are ideal for gathering standardized responses that facilitate quantitative analysis (Greener, 2008). Structured questionnaires are particularly effective for this study because they enable the collection of specific, measurable data on the adoption of artificial intelligence, blockchain, and machine learning in credit analysis, while maintaining consistency across respondents (Schindler, 2022). The questionnaires included items measured on a Likert scale, focusing on the indicators of the study variables. For each indicator, an average of the Likert scale responses was computed to generate a composite score for analysis. The questionnaire consisted of three sections. Section A focused on the demographic profile of respondents. Section B collected data on technology characteristics while section C will collect data on the extent of adoption of emerging technologies. Therefore, data for the variables of technology characteristics and extent of adoption of emerging technologies came from primary data. The construction of the questionnaire was informed by existing instruments validated in previous studies, including Rahman et al. (2023), Neumann et al. (2024), and Noriega et al. (2023). For instance, items measuring technology characteristics such as relative advantage, trust, complexity, compatibility, and security were adapted from studies on technology adoption in financial services. Similarly, items measuring the extent of adoption were designed to capture the usage of AI, blockchain, and machine learning in various aspects of credit analysis.

The questionnaires were distributed both physically and via email using the contact details of DTSs provided by SASRA (2024). To enhance the response rate, trained research assistants were engaged to follow up with respondents and provide guidance during questionnaire completion. For physical distribution, questionnaires were sent to the SACCOs and collected after two weeks while email reminders will be used for online distribution.

Data for financial capacity and board characteristics were collected from secondary data, which were obtained by reviewing the 2024 annual reports of the SACCOs. This was appropriate since indicators such as profitability, board size, and capital adequacy are objective measures better captured from audited reports than through self-reports. This data provided supplementary information on institutional characteristics, which include financial capacity (profitability, asset quality and capital adequacy) and board characteristics (board size, board independence and board diversity). The combination of these data collection methods will facilitate a comprehensive exploration of the study's objectives while ensuring data accuracy and reliability.

3.7 Research Quality

3.7.1 Validity

Validity refers to the extent to which a research instrument measures what it is intended to measure (Greener, 2008). To ensure validity in this study, several steps will be taken. First, a pilot survey was conducted with 15 respondents from DTSs who are not part of the main study sample. This pilot test helped identify any ambiguities or inconsistencies in the questionnaire, ensuring clarity and appropriateness of the items. Feedback from the pilot survey was used to refine the questionnaire. Second, the questionnaire was subjected to expert review by a supervisor at Strathmore University. This review ensured that the questionnaire items align with the study’s objectives and accurately measure the variables of interest. These steps enhanced both the content and construct validity of the research instrument.

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3.7.2 Reliability

Reliability refers to the consistency of a research instrument in measuring a concept across repeated trials (Raju & Prabhu, 2019). In this study, reliability will be assessed using Cronbach's alpha, which evaluates the internal consistency of the questionnaire items. Schindler (2022) suggest that a Cronbach's alpha value of 0.70 and above is acceptable, while values above 0.80 are considered good and above 0.90 are excellent. Raju and Prabhu (2019) recommend a minimum threshold of 0.70 while Zikmund et al. (2013) propose that a value between 0.60 and 0.70 is acceptable but 0.70 and above is preferable. For this study, the recommendation by Schindler (2022) was adopted, with a threshold of 0.70 and above deemed acceptable for ensuring reliability. Table 3.1 shows the reliability statistics for the questionnaire.

Table 3. 1: Reliability Statistics

Variable	Cronbach's Alpha Coefficient	Number of Items	Interpretation
Technology Characteristics	0.858	15	Reliable
Extent of adoption	0.958	15	Reliable

Source: Researcher (2015)

3.8 Data Analysis

The data analysis process began with data cleaning, which involved checking for missing data, outliers, and inconsistencies. This ensures the dataset is complete, accurate, and suitable for analysis. The cleaned data was entered into Statistical Package for Social Sciences (SPSS) software that was used for both descriptive and inferential analysis. Descriptive statistics was employed to summarize the data. For continuous variables, means and standard deviations were calculated, while categorical data was summarized using frequencies and percentages. These statistics provided insights into the extent of adoption of emerging technologies and the characteristics of the SACCOs under study. Inferential statistics included the use of multiple linear regression to examine the relationship between the adoption of emerging technologies (dependent variable) and the independent variables: financial capacity, board characteristics and technology characteristics. The regression model estimated the influence of each independent variable on the dependent variable while controlling for other variables.

The linear regression model equation for this study will be as follows:

$$EA = \beta_0 + \beta_1 FF + \beta_2 GC + \beta_3 TC + \epsilon$$

- *EA* is the dependent variable (extent of adoption of emerging technologies).
- β0 is the constant
- FF = Financial capacity
- GC = Board characteristics
- TC = Technology Characteristics

3.9 Ethical Considerations

Prior to data collection, ethical approval was obtained from the National Commission for Science, Technology and Innovation (NACOSTI) and the ethical review committee at Strathmore University. Confidentiality was maintained by anonymizing participants and safeguarding any identifying information, which was stored in password-protected files accessible only to the researcher. The privacy of participants was respected throughout the study, ensuring that personal information is not shared or used beyond the research purpose. Informed consent was sought from all participants, clearly outlining the study's objectives, procedures, and the voluntary nature of participation. Participants were assured of their right to withdraw from the study at any time without consequences, and their identities remained confidential. The findings will be disseminated to the SACCOs that will have participated in this research.

3.10 Chapter Summary

This chapter has presented the methodology that was adopted for the proposed study. The research philosophy, design, population, sampling design, data collection methods, research quality including validity and reliability, data analysis, and ethical considerations, have been elaborated in this chapter.

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CHAPTER FOUR

PRESENTATION OF RESULTS

4.1 Introduction

This study sought to examine the factors that influence the adoption of emerging technologies, including artificial intelligence, block chain, and machine learning, in credit analysis among DTSs in Kenya. The factors of interest were financial capacity, board characteristics, and technology characteristics. In this chapter, the results of both secondary research and primary research conducted using the survey approach are presented. The chapter begins with presenting the response rate, respondents' demographic data, descriptive analysis and inferential analysis.

4.2 Response Rate

The questionnaire was sent to all 177 DTSs in Kenya; however, only 110 complete responses were collected after a period of one month. This translates to a response rate of 62%, which according to Bell et al. (2022), is adequate to proceed with the analysis since the minimum threshold for obtaining generalizable results is 60%. Secondary data was collected from the 2024 annual reports of the DTSs that responded to the survey such that the data from secondary research was paired with the data from the primary research. Table 4.1 shows the response rate.

Table 4. 1: Response Rate

Category	Frequency	Percentage
Questionnaires sent	177	100%
Complete questionnaires received	110	62%
Unreturned questionnaires	67	38%

Source: Researcher (2025)

4.3 Respondents' Demographic Data

The study included 110 respondents from Deposit-Taking SACCOs (DTSs) in Kenya. Males made up the majority (65%, n = 72), while females accounted for 35% (n = 38). Most participants were aged 35–44 years (55%, n = 60), followed by 25–34 years (30%, n = 33). No respondents were under 25 or over 54.

In terms of education, 66% (n = 73) held undergraduate degrees, while 34% (n = 37) had postgraduate qualifications. None reported only a certificate or diploma. Regarding job positions, managers were the largest group (65%, n = 71), followed by assistant managers (12%, n = 13) and credit officers (13%, n = 14). Other roles, such as ICT assistants (5%, n = 5) and procurement officers (3%, n = 3), had smaller representation.

Work experience varied. 31% (n = 34) had over 10 years of service, while 25% (n = 28) had 7–10 years. Only 5% (n = 5) had been in their SACCO for less than one year. Most respondents worked in financial-sector SACCOs (76%, n = 84), with smaller groups in housing (10%, n = 11), transport (5%, n = 5), and agriculture (5%, n = 5).

The majority of SACCOs had more than 5,000 members (75%, n = 82), while 7% (n = 8) had 500–1,000 members. Annual turnover showed a similar trend where 62% (n = 68) reported over Ksh 500 million, and 34% (n = 37) fell between Ksh 50–100 million. No SACCOs had a turnover between Ksh 100–500 million.

This demographic profile indicates a sample primarily composed of experienced, highly educated professionals from large, financially stable SACCOs, most of which operate in the financial sector. These findings may reflect the perspectives of well-established institutions rather than smaller or newer ones. Table 4.2 presents the demographic data for the respondents in this study.

Table 4. 2: Demographic Data

		Count	Percent
Gender	Female	38	35%
	Male	72	65%
	Total	110	100%
Age	18-24	0	0%
	25-34	33	30%
	35-44	60	55%
	45-54	17	15%
	55 and above	0	0%
	Total	110	100%
Highest level of education completed	Certificate/Diploma	0	0%
	Undergraduate degree	73	66%
	Postgraduate degree	37	34%
	Total	110	100%
Position in the SACCO	Manager	71	65%
	Assistant Manager	13	12%

	Credit Officer	14	13%
	Operations Officer	4	4%
	ICT Assistant	5	5%
	Procurement Officer	3	3%
	Total	110	100%
Number of years worked in the SACCO	Less than 1 year	5	5%
	1-3 years	21	19%
	4-6 years	22	20%
	7-10 years	28	25%
	More than 10 years	34	31%
	Total	110	100%
Sector of SACCO	Agricultural	5	5%
	Transport	5	5%
	Housing	11	10%
	Financial	84	76%
	Energy	5	5%
	Total	110	100%
Size of the SACCO (Based on total membership)	Less than 500 members	0	0%
	500-1000 members	8	7%
	1001-5000 members	20	18%
	More than 5000 members	82	75%
	Total	110	100%
Annual Turnover of the SACCO	Less than Ksh 50 million	5	5%
	Ksh 50 million - Ksh 100 million	37	34%
	Ksh 100 million - Ksh 500 million	0	0%
	More than Ksh 500 million	68	62%
	Total	110	100%

Source: Researcher (2025)

4.4 Descriptive Analysis

The descriptive statistics of the variables examined in this study are presented in this chapter. These variables include financial capacity, board characteristics, technology characteristics, and the extent of adoption.

4.4.1 Descriptive Statistics for Financial capacity

The first objective was to examine the influence of financial capacity, including profitability (ratio of total revenue minus operating expenses divided by total revenue), asset quality (provision coverage ratio), and capital adequacy (capital adequacy ratio) on the extent of adoption of emerging technologies in credit analysis by DTSs. A composite score for financial capacity was computed using a mean such that a high score indicated that the SACCO had a stronger financial position and vice versa.

For profitability (calculated as total revenue minus operating expenses divided by total revenue), the mean score was 0.102 (SD = 0.028). This suggests that, on average, SACCOs retained about 10.2% of their revenue after covering operating costs. Asset quality, measured by the provision coverage ratio, averaged 0.645 (SD = 0.158). This indicates that most SACCOs had set aside 64.5% of the required provisions for potential loan losses. The capital adequacy ratio, reflecting financial stability, had a mean of 0.136 (SD = 0.042). This means SACCOs maintained capital reserves at 13.6% of risk-weighted assets, exceeding the regulatory minimum in many jurisdictions. The composite financial capacity score averaged 0.294 (SD = 0.075) across all SACCOs. The relatively low standard deviations suggest limited variability in financial performance among the sampled institutions. These findings indicate that most SACCOs in the study were moderately profitable, maintained reasonable loan loss provisions, and met capital adequacy requirements. These findings are presented in Table 4.3.

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Table 4. 3: Descriptive Statistics for Financial capacity

	N	Mean	Std. Deviation
Ratio of total revenue minus operating expenses divided by the total revenue	110	.1017	.02815
Provision Coverage Ratio	110	.6452	.15830
Capital adequacy ratio	110	.1356	.04216
Financial capacity	110	.2942	.07473

Source: Researcher (2025)

4.4.2 Board characteristics

The second objective was to examine the influence of board characteristics on board size (number of board members), board independence (proportion of independent directors on a board), and board diversity (proportion of female directors to total directors) on the extent of adoption of emerging technologies in credit analysis by DTS. A composite score was calculated for board characteristics using standardized values (z-scores) in order to address the issue of scale differences because the variables measured in different units (board size in absolute numbers, independent directors and diversity in percentages/proportions. Such an approach ensures that each variable contributes meaningfully to the composite score.

Board size averaged 8.99 members (SD = 2.71), showing most SACCOs had between 6-12 directors. Board independence (proportion of independent directors) showed a mean of 33.9% (SD = 15.7%), indicating about one-third of board seats were held by independent members. Gender diversity was lower, with female directors comprising 19.3% (SD = 11.3%) of boards on average. This suggests male directors still dominate SACCO governance structures. The composite board characteristics score had a mean near zero (0.015, SD = 0.921), as expected with z-score standardization. The relatively large standard deviation indicates substantial variation in board characteristics across SACCOs compared to financial capacity. Overall, these findings reveal that SACCO boards are moderately sized (around 9 members), independent directors occupy about one-third of seats, gender diversity remains limited (under 20% female representation), and that governance practices vary significantly between institutions. Table 4.4 depicts these findings.

Table 4. 4: Descriptive Statistics for Board characteristics

	N	Mean	Std. Deviation
Board Size	110	8.9909	2.70743
Board independence	110	.3394	.15651
Board Diversity	110	.1925	.11252
Board characteristics	110	.0147	.92115

Source: Researcher (2025)

4.4.3 Descriptive Statistics on Technology Characteristics

The third objective was to examine the influence of technology characteristics on the extent of adoption of emerging technologies in credit analysis by DTSs in Kenya. The technology characteristics examined in this study were relative advantage, trust, compatibility, security and complexity of these emerging technologies, which were measured using a five-point Likert scale that ranges from 1 (strongly disagree) to 5 (strongly disagree). Items on complexity were reverse coded to ensure consistency in the direction of the scale. A composite score was also calculated using the mean of the items such that a high score indicated favorable technology characteristics and vice versa.

The statement "Senior management believes that the adoption of artificial intelligence (AI) will significantly improve credit analysis processes" received a mean score of 4.52 with a standard deviation of 0.83. This indicates strong agreement among respondents about AI's potential benefits. For machine learning, the statement "Senior management perceives machine learning (ML) as a tool that will provide a competitive advantage in credit analysis" scored slightly lower at 4.30 (SD=0.91), still reflecting positive perceptions. Regarding blockchain, the view that "The use of blockchain technology is seen by senior management as beneficial for enhancing transparency and security in credit analysis" obtained a mean of 3.85 (SD=1.21), suggesting more moderate agreement with greater variability in responses.

Trust in AI was measured by the statement "Senior management has a high level of trust in the ability of artificial intelligence (AI) to accurately assess credit risk," which yielded a mean of 3.98 (SD=0.94). The statement "Senior management believes that machine learning (ML) algorithms can be trusted to make reliable credit decisions" scored higher at 4.19 (SD=0.88), showing relatively strong confidence. For blockchain, the item "Senior management feels confident in the security and reliability of blockchain for preventing fraud in credit analysis" received a mean of 3.68 (SD=0.99), indicating more reserved trust levels.

The compatibility of AI was assessed through "Senior management believes that artificial intelligence (AI) is compatible with the existing credit analysis processes in the SACCO," scoring 3.53 (SD=0.97). ML compatibility, as measured by "The use of machine learning (ML) is seen as compatible with the SACCO's current technological infrastructure and systems," showed a slightly higher mean of 3.70 (SD=1.07). For blockchain, the statement "Senior management perceives blockchain technology as compatible with the SACCO's operational processes in credit analysis" obtained a mean of 3.59 (SD=1.09).

Regarding AI security, the statement "Senior management believes that artificial intelligence (AI) tools used in credit analysis provide sufficient data protection" received a mean of 3.38 (SD=1.11). For ML, the item "Senior management considers machine learning (ML) algorithms to be secure in handling sensitive customer data in credit analysis" scored 3.42 (SD=1.13). Blockchain security perceptions, measured by "Senior management views blockchain technology as providing a highly secure method for storing and verifying credit-related transactions," showed a mean of 3.49 (SD=1.09).

The complexity of AI implementation was captured by "Senior management believes that the implementation of artificial intelligence (AI) for credit analysis is complex and requires substantial effort to integrate," which scored lowest at 2.34 (SD=1.21). For ML, the statement "Senior management considers machine learning (ML) to be a complex technology that is challenging to adopt in credit analysis" received a mean of 2.95 (SD=1.17). Regarding blockchain, the view that "Senior management perceives blockchain technology as complex, making it difficult to implement in the SACCO's credit analysis processes" obtained a mean of 3.05 (SD=1.03).

The data reveals clear patterns in management perceptions. AI and ML received the strongest endorsement for relative advantage, with AI's process improvement scoring highest overall (M = 4.52). Trust levels followed a similar pattern, though with slightly lower scores, particularly for blockchain's fraud prevention capabilities (3.68). The standard deviations (ranging 0.83-1.21) indicate moderate consensus among respondents, with blockchain opinions showing the most variability.

Compatibility and security perceptions clustered in the mid-range (3.38-3.70), suggesting cautious optimism about technological fit but lingering concerns. Notably, all security-related items scored below 3.5, with AI data protection receiving the lowest marks (3.38). Complexity concerns were pronounced, especially for AI implementation (M = 2.34), though blockchain was perceived as marginally more difficult than ML to adopt.

These findings suggest that while SACCO leadership recognizes the transformative potential of emerging technologies - particularly AI and ML - practical concerns about implementation challenges and security risks may slow adoption. The descriptive findings for technology characteristics are presented in Table 4.5.

Table 4. 5: Descriptive statistics for technology characteristics

	N	Mean	Std. Deviation
Senior management believes that the adoption of artificial intelligence (AI) will significantly improve credit analysis processes.	110	4.52	.832
Senior management perceives machine learning (ML) as a tool that will provide a competitive advantage in credit analysis.	110	4.30	.914
The use of blockchain technology is seen by senior management as beneficial for enhancing transparency and security in credit analysis	110	3.85	1.210
Senior management has a high level of trust in the ability of artificial intelligence (AI) to accurately assess credit risk.	110	3.98	.938
Senior management believes that machine learning (ML) algorithms can be trusted to make reliable credit decisions.	110	4.19	.883
Senior management feels confident in the security and reliability of blockchain for preventing fraud in credit analysis.	110	3.68	.995
Senior management believes that artificial intelligence (AI) is compatible with the existing credit analysis processes in the SACCO.	110	3.53	.974
The use of machine learning (ML) is seen as compatible with the SACCO's current technological infrastructure and systems.	110	3.70	1.071
Senior management perceives blockchain technology as compatible with the SACCO's operational processes in credit analysis.	110	3.59	1.086
Senior management believes that artificial intelligence (AI) tools used in credit analysis provide sufficient data protection.	110	3.38	1.109
Senior management considers machine learning (ML) algorithms to be secure in handling sensitive customer data in credit analysis.	110	3.42	1.128
Senior management views blockchain technology as providing a highly secure method for storing and verifying credit-related transactions.	110	3.49	1.090
Senior management believes that the implementation of artificial intelligence (AI) for credit analysis is complex and requires substantial effort to integrate.	110	2.34	1.214
Senior management considers machine learning (ML) to be a complex technology that is challenging to adopt in credit analysis.	110	2.95	1.172

Senior management perceives blockchain technology as complex, making it difficult to implement in the SACCO's credit analysis processes.	110	3.05	1.030

Source: Researcher (2025)

4.4.4 Descriptive Statistics on the Extent of Adoption of Emerging Technologies

The extent of adoption of emerging technologies was the dependent variable in this study, which was measured using five-point Likert scales that range from strongly disagree (1) to strongly agree (5). A composite score was also computed using the mean of the average such that a high score indicates a high level of adoption and vice versa.

The statement "The SACCO uses AI tools to analyze member creditworthiness and make lending decisions" received a mean score of 2.85 (SD=1.31). This suggests moderate adoption, with significant variation among respondents. For credit risk management, "AI systems are used in the SACCO to predict loan defaults and manage credit risk" scored similarly at 2.87 (SD=1.23). The comparable scores indicate consistent AI application across these credit functions. Customer service applications showed slightly lower adoption with "The SACCO employs AI-powered chatbots to provide real-time customer support" at 3.17 (SD=1.26). The higher mean suggests this may be a newer or less prioritized application.

"Fraud detection in the SACCO is enhanced through AI-based monitoring systems" scored 3.55 (SD=1.15), indicating more established use. The lower standard deviation suggests greater consensus about this application. For process automation, "AI tools are used in the SACCO to automate routine tasks like loan application processing" received a mean of 3.37 (SD=1.07). This shows moderate adoption with relatively consistent views across respondents.

"Machine learning models are used in the SACCO to identify patterns in member savings and borrowing behavior" scored 3.45 (SD=1.19). The score reflects growing but not universal adoption. "The SACCO uses machine learning algorithms to optimize loan approval processes" showed similar adoption at 3.39 (SD=1.17). The parallel scores suggest consistent ML implementation across credit functions. For forecasting, "Predictive analytics powered by machine learning is used in the SACCO for financial forecasting" scored 3.46 (SD=1.12). The slightly higher mean may indicate greater value seen in this application.

"Machine learning helps the SACCO personalize financial products based on members' past transactions" received a mean of 3.50 (SD=1.03). The relatively high score suggests personalization is a priority application. "Member retention strategies in the SACCO are guided by insights generated from machine learning models" scored 3.52 (SD=1.21). This shows comparable adoption to other ML uses, with slightly more variation in responses.

"The SACCO uses blockchain to maintain secure and tamper-proof transaction records" scored 3.25 (SD=1.19). This indicates emerging but not yet widespread adoption. For smart contracts, "Blockchain technology is applied in the SACCO to automate loan agreements through smart contracts" received a mean of 3.18 (SD=1.12). The similar score suggests parallel adoption across blockchain applications. "Digital identities based on blockchain are used in the SACCO to streamline member verification processes" scored 3.28 (SD=1.17). The slightly higher mean may reflect stronger perceived benefits for identity management.

"Blockchain systems in the SACCO enhance transparency and build member trust" received a mean of 3.48 (SD=1.08). This higher score suggests greater recognition of blockchain's trust-building potential. "The use of blockchain has improved the speed and accuracy of financial transactions in the SACCO" scored 3.35 (SD=1.24). The comparable mean but higher variability indicates mixed experiences with transactional benefits.

The composite "Extent of Adoption" score averaged 3.31 (SD=0.93). This suggests moderate overall adoption, with the standard deviation indicating meaningful variation across SACCOs. AI and ML applications generally scored higher than blockchain, though all technologies showed room for increased adoption. Fraud detection and member retention emerged as relatively stronger use cases, while customer-facing AI applications like chatbots showed lower adoption. The results suggest an emerging but uneven technology integration in credit operations. Table 4.6 presents these descriptive statistics.

Table 4. 6: Descriptive Statistics for the extent of adoption of emerging technologies

	N	Mean	Std. Deviation
The SACCO uses AI tools to analyze member creditworthiness and make lending decisions	110	2.85	1.305
AI systems are used in the SACCO to predict loan defaults and manage credit risk	110	2.87	1.227

The SACCO employs AI-powered chatbots to provide real-time customer support.	110	3.17	1.255
Fraud detection in the SACCO is enhanced through AI-based monitoring systems.	110	3.55	1.154
AI tools are used in the SACCO to automate routine tasks like loan application processing.	110	3.37	1.074
Machine learning models are used in the SACCO to identify patterns in member savings and borrowing behavior.	110	3.45	1.185
The SACCO uses machine learning algorithms to optimize loan approval processes.	110	3.39	1.174
Predictive analytics powered by machine learning is used in the SACCO for financial forecasting	110	3.46	1.123
Machine learning helps the SACCO personalize financial products based on members' past transactions	110	3.50	1.029
Member retention strategies in the SACCO are guided by insights generated from machine learning models.	110	3.52	1.210
The SACCO uses blockchain to maintain secure and tamper-proof transaction records.	110	3.25	1.190
Blockchain technology is applied in the SACCO to automate loan agreements through smart contracts.	110	3.18	1.119
Digital identities based on blockchain are used in the SACCO to streamline member verification processes.	110	3.28	1.166
Blockchain systems in the SACCO enhance transparency and build member trust	110	3.48	1.081
The use of blockchain has improved the speed and accuracy of financial transactions in the SACCO	110	3.35	1.238
Extent of Adoption	110	3.3121	.92834

Source: Researcher (2025)

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4.5 Inferential Statistics

4.5.1 Correlations

The correlation analysis reveals an extremely strong positive correlation between financial capacity and board characteristics ($r = 0.884$, $p < 0.05$). This highly significant relationship indicates that SACCOs with stronger financial positions may have better governance structures. The strong correlation suggests these institutional factors develop in tandem within Kenya's SACCO sector, with each potentially reinforcing the other.

Both financial capacity ($r = 0.913$, $p < 0.05$) and board characteristics ($r = 0.927$, $p < 0.05$) demonstrate remarkably strong correlations with technology adoption. These statistically significant results confirm that financially stable SACCOs with robust governance are substantially more likely to implement emerging technologies.

While still statistically significant ($p < 0.05$), the correlations involving technology characteristics are notably weaker. The relationship with financial capacity ($r = 0.498$) and board characteristics ($r = 0.557$) suggests that positive technology perceptions are somewhat associated with stronger institutional capacity, but not as strongly as actual adoption patterns. Similarly, the moderate correlation between technology characteristics and adoption ($r = 0.491$, $p < 0.05$) indicates that favorable perceptions contribute to, but do not guarantee, implementation. These correlations statistics are presented in Table 4.7

Table 4. 7: Correlations

		Financial capacity	Board characteristics	Technology Characteristics	Extent of Adoption
Financial capacity	r	1			
	p				
Board characteristics	r	.884**	1		
	p	.000			
Technology Characteristics	r	.498**	.557**	1	
	p	110	110	110	
Extent of Adoption	r	.913**	.927**	.491**	1
	p	.000	.000	.000	

Source: Researcher (2025)

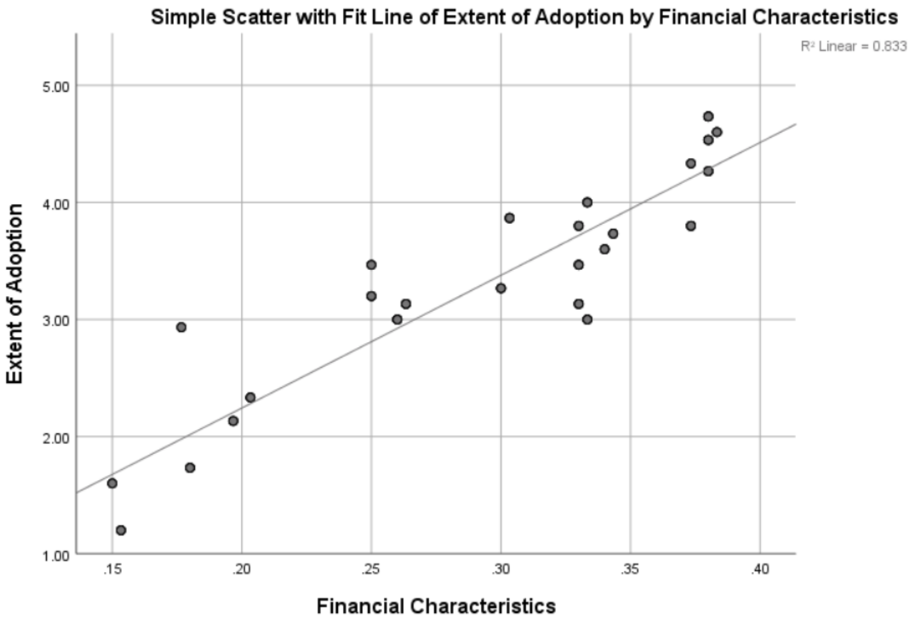
4.5.2 Regression Analysis

A multiple regression analysis was performed to determine if financial capacity, board characteristics and technology characteristics are significant predictors of the extent of adoption of emerging technologies.

4.5.2.1 Diagnostic Tests

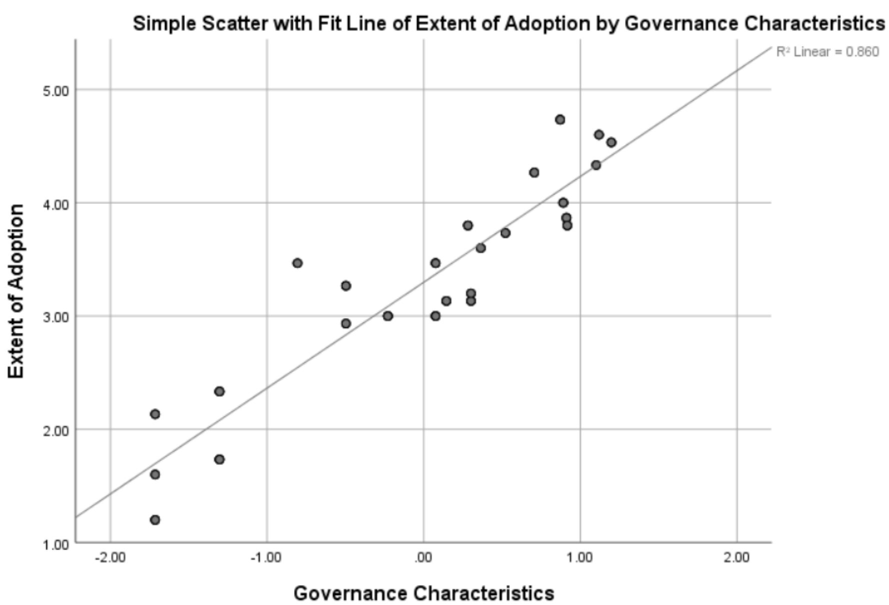
The data was first tested to see if it meets the assumption of linearity, which requires that a linear association should be present between independent and dependent variables. Linearity can be determined by looking at the scatter plots, such that data points that are close to the fit line affirms this assumption. These are shown in Figures 4.1, 4.2 and 4.3.

Figure 4. 1: Scatter Plot - Extent of Adoption by Financial capacity



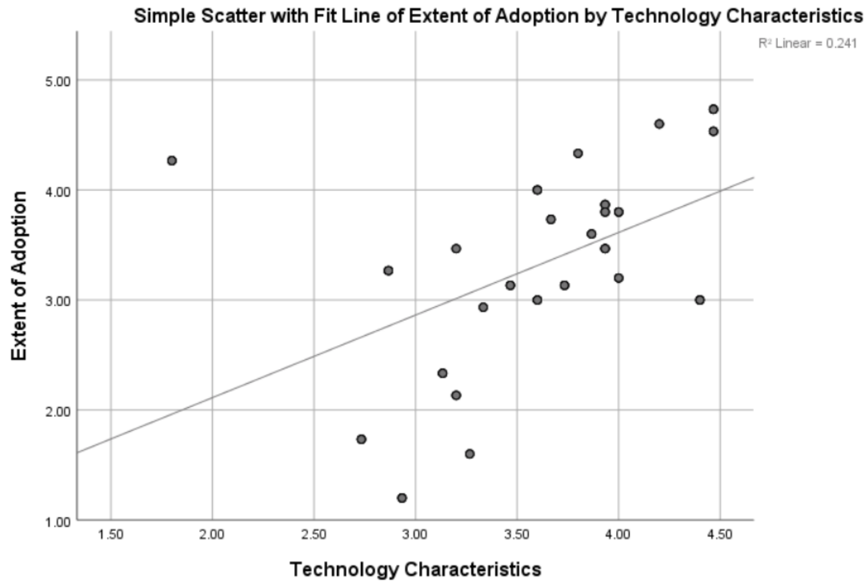
Source: Researcher (2025)

Figure 4. 2: Scatter Plot: Extent of Adoption by Board characteristics
Source: Researcher (2025)



Source: Researcher (2025)

Figure 4. 3: Scatter Plot: Extent of Adoption by Technology Characteristics



Source: Researcher (2025)

The data was also checked for normality. This was performed using the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk Tests, such that significance that is greater than 0.05 indicates normal distribution.

The results of the normality tests indicate that all variables in the study follow a normal distribution. For financial capacity, both the Kolmogorov-Smirnov test (statistic = 0.211, p = 0.312) and Shapiro-Wilk test (statistic = 0.888, p = 0.257) produced non-significant results, confirming the data's normal distribution. Similarly, board characteristics showed no deviation from normality, with the Kolmogorov-Smirnov test yielding a statistic of 0.181 (p = 0.175) and the Shapiro-Wilk test showing a statistic of 0.892 (p = 0.263).

The technology characteristics variable also demonstrated normal distribution, as evidenced by the Kolmogorov-Smirnov test result of 0.119 (p = 0.561) and Shapiro-Wilk test result of 0.932 (p = 0.280). The extent of technology adoption, the study's dependent variable, similarly met the normality assumption with a Kolmogorov-Smirnov statistic of 0.142 (p = 0.121) and Shapiro-Wilk statistic of 0.941 (p = 0.112).

These consistent findings across all variables suggest that parametric statistical methods are appropriate for analyzing the data. The agreement between both normality tests for each variable strengthens confidence in these results. The normal distribution of the extent of adoption variable is particularly important, as it serves as the primary outcome measure in the study. The results indicate that no data transformations are necessary before proceeding with further statistical analyses.

Table 4. 8: Normality Tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Financial capacity	.211	110	.312	.888	110	.257
Board characteristics	.181	110	.175	.892	110	.263
Technology Characteristics	.119	110	.561	.932	110	.280
Extent of Adoption	.142	110	.121	.941	110	.112
a. Lilliefors Significance Correction						

4.5.2.2 Multiple Regression Analysis

The regression analysis demonstrates a robust predictive relationship between the independent variables (financial capacity, board characteristics, and technology characteristics) and the dependent variable (extent of adoption of emerging technologies) as shown in Table 4.9. The model exhibits exceptional explanatory power, as evidenced by the key fit statistics. The multiple correlation coefficient ($R = 0.949$) indicates an extremely strong linear association between the predictor variables and technology adoption levels. The coefficient of determination ($R^2 = 0.901$) reveals that the model accounts for 90.1% of the variance in technology adoption, suggesting that the combination of financial capacity, board characteristics, and technological factors explains nearly all observable variation in adoption behavior among SACCOs. The standard error of the estimate (0.297) demonstrates good predictive precision, with relatively small deviations between predicted and observed values of technology adoption.

Table 4. 9: Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.949[a]	.901	.898	.29685
a. Predictors: (Constant), Technology Characteristics, Financial capacity, Board characteristics				
b. Dependent Variable: Extent of Adoption				

Source: Researcher (2025)

The ANOVA table presents the significance test for the overall regression model examining the relationship between financial capacity, board characteristics, technology characteristics, and the extent of technology adoption. The extremely significant F-statistic ($F = 320.010$, $p < .05$) indicates that the regression model provides a statistically significant improvement over using the mean to predict technology adoption. The probability of obtaining such results by chance alone is less than .001, providing strong evidence against the null hypothesis that the predictors have no effect. The model explains a substantial portion of variance in technology adoption, with the regression sum of squares (84.597) accounting for most of the total variation (93.937). This corresponds to the high R^2 value observed in the model summary, confirming the model's strong explanatory power. The large F-value (320.010) relative to the residual mean square (.088) suggests that the explained variance is substantially greater than the unexplained variance. This indicates a very strong relationship between the predictor variables and technology adoption. The small residual sum of squares (9.341) relative to the regression sum of squares further confirms the model's excellent fit to the data. The mean square error of .088 suggests relatively precise estimation. Table 4.10 shows these findings.

Table 4. 10: Regression ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	84.597	3	28.199	320.010	.000[b]
	Residual	9.341	106	.088		
	Total	93.937	109			
a. Dependent Variable: Extent of Adoption						
b. Predictors: (Constant), Technology Characteristics, Financial capacity, Board characteristics						

Source: Researcher (2025)

The coefficients table presents both unstandardized and standardized regression results for the three predictors of technology adoption (Table 4.11). The standardized coefficients (Beta values) were used because they allow direct comparison of each predictor's relative importance by putting them on the same scale (mean = 0, SD = 1). This is particularly valuable when predictors have different measurement units, as in this study where financial capacity (ratios), board characteristics (standardized scores), and technology characteristics (Likert scales) were measured differently.

The standardized coefficients reveal that board characteristics (β = .572) had the strongest unique contribution to predicting technology adoption, followed by financial capacity (β = .428). Technology characteristics showed a non-significant negative relationship (β = -.041, p = .272), suggesting that when controlling for financial capacity, board characteristics, technology perceptions did not independently predict adoption.

The Variance Inflation Factors (VIF) indicate moderate multicollinearity between financial and board characteristics (VIF = 4.579 and 4.988 respectively), which is expected given their conceptual overlap in organizational research. While these values exceed the common threshold of 2-3, they remain below the more conservative cutoff of 5, suggesting the multicollinearity, while present, does not severely compromise the results. Technology characteristics showed minimal multicollinearity (VIF = 1.45), confirming its independence from the other predictors.

The tolerance statistics (1/VIF) mirror these findings, with financial and board characteristics showing reduced tolerance (.218 and .200 respectively), indicating shared variance between these predictors. The significant t-values for financial (t = 6.523, p < .05) and board characteristics (t = 8.361, p < .05) confirm their robust independent contributions, while technology characteristics failed to reach significance (t = -1.104, p = .272).

These results suggest that while financial capacity and board characteristics are strong, independent predictors of technology adoption, their predictive power is somewhat interrelated. The non-significant technology characteristics coefficient indicates that its apparent bivariate relationship with adoption (from earlier correlations) may have been largely accounted for by financial capacity and board characteristics in the multivariate model. The new regression model based on the findings of the multiple regression is:

$$EA = 0.428\text{FF} + 0.572\text{GC} + \in$$

Table 4. 11: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.965	.312		6.300	.000		

	Financial capacity	5.311	.814	.428	6.523	.000	.218	4.579
	Board characteristics	.576	.069	.572	8.361	.000	.200	4.988
	Technology Characteristics	-.062	.056	-.041	-1.104	.272	.690	1.450

a. Dependent Variable: Extent of Adoption

Source: Researcher (2025)

4.6 Chapter Summary

This chapter has presented the results of this study. The regression analysis revealed that board characteristics ($\beta = .572$, $p < .05$) and financial capacity ($\beta = .428$, $p < .05$) were strong, statistically significant predictors of technology adoption, with board characteristics showing slightly greater influence. Technology characteristics did not demonstrate a significant independent effect ($\beta = -.041$, $p = .272$) when controlling for the other factors. Moderate multicollinearity between financial and board predictors was observed but did not invalidate the results.

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CHAPTER FIVE

DISCUSSION, CONCLUSION, AND RECOMENDATIONS

5.1 Introduction

This chapter discusses the main findings and provides recommendations. The chapter commences with a summary of the main results, followed by a discussion and then recommendations. Additionally, the limitations of the study and recommendations for further research are presented in this chapter.

5.2 Summary of Main Results

The first objective examined the influence of financial capacity on technology adoption. The findings revealed a very strong positive relationship, indicating that SACCOs with better financial health were significantly more likely to adopt emerging technologies. Financial capacity emerged as one of the strongest predictors in the regression analysis, confirming its crucial role in enabling technological investment and implementation. For the second objective regarding board characteristics, the results showed an equally strong association with technology adoption. Well-governed SACCOs demonstrated substantially higher adoption rates, with board characteristics proving to be the single most influential factor in the regression model. The third objective focused on technology characteristics and produced more nuanced findings. While initial correlations showed a moderate positive relationship between favorable technology perceptions and adoption, this association disappeared in the regression analysis when accounting for financial capacity and board characteristics. This indicates that positive attitudes toward technology may only translate into actual adoption when supported by adequate institutional capacity.

5.3 Discussion of Findings

5.3.1 Financial capacity and the Extent of Adoption of Emerging Technologies

The first objective of the study was to examine the influence of financial capacity, specifically profitability, asset quality, and capital adequacy, on the extent of adoption of emerging technologies in credit analysis by Deposit-Taking SACCOs (DTSs) in Kenya. The regression results confirmed a statistically significant and positive relationship between financial health and the adoption of technologies such as AI, machine learning (ML), and blockchain. These findings affirm the Technology-Organization-Environment (TOE) framework, which suggests that organizational readiness, including financial capacity, is a key determinant of successful technology integration (Tornatzky & Fleischer, 1990; Awa et al., 2017).

In this context, profitability serves as a crucial indicator of a SACCO's ability to invest in emerging technology. Institutions with higher profit margins are better positioned to finance upfront technology acquisition, staff training, and system maintenance. This aligns with previous research by Noriega et al. (2023) and Gupta et al. (2022), which found that financially sound organizations are more likely to prioritize technology investments that improve operational efficiency and reduce credit risk. In this study, profitable SACCOs reported more advanced use of digital credit scoring tools, automated risk assessment models, and integration with blockchain systems for transaction transparency; thus, highlighting how internal resource strength enables digital innovation.

Asset quality, measured through non-performing loans (NPLs), was inversely related to technology adoption. SACCOs with lower levels of NPLs were more likely to adopt emerging technologies. This finding supports the notion that institutions with better credit risk profiles have more financial stability and lower provisioning costs, freeing up capital for innovation. It also reflects the findings of Majumder (2023), who noted that reduced credit risk from prior periods often enabled banks to deploy AI tools in risk management. Conversely, institutions burdened by high NPLs may be forced to allocate financial and managerial resources toward recovery strategies, leaving limited bandwidth for adopting emerging technologies.

Capital adequacy, the cushion available to absorb potential losses, also had a significant positive effect on technology adoption. SACCOs with stronger capital positions were more confident in pursuing technological innovations, perceiving them as manageable risks rather than costly experiments. This echoes insights from Gupta et al. (2022), who argued that higher capital ratios correlate with a greater willingness to invest in digital transformation. The presence of robust capital reserves serves not only as a financial buffer but also as a strategic asset that allows SACCOs to explore transformative solutions without jeopardizing core operations.

Collectively, these findings indicate that financial capacity are foundational in enabling or constraining the adoption of digital tools in credit analysis. The results are consistent with the TOE framework’s organizational context, which emphasizes that internal resources, including financial strength, must be aligned with technology characteristics and environmental conditions to support innovation (Oliveira & Martins, 2011; Rambe et al., 2022). The study confirms that SACCOs do not adopt technologies in isolation but instead weigh such decisions against their financial capabilities and operational priorities.

These findings also contribute new evidence to a largely underexplored sector. Existing literature, such as that by Rane et al. (2023), Hoque et al. (2024), and Bouteraa et al. (2024), has frequently emphasized cost as a barrier to adoption but has often failed to explicitly measure the internal financial characteristics of organizations. While these studies noted the high costs of implementation and lack of financial support as challenges, they did not analyze how specific financial indicators like profitability or capital adequacy influence adoption behavior. This study fills that gap by directly linking financial health to technology integration in the SACCO context, thus providing a more granular understanding of financial enablers of innovation.

Moreover, these findings challenge assumptions in some literature that technology adoption is primarily driven by institutional attitudes or external regulation. While such factors are undoubtedly important, the data suggests that even the most forward-looking leadership or policy frameworks may struggle to gain traction without adequate financial support at the institutional level. In line with the TOE framework, this suggests that external pressures (environment) and internal enthusiasm (organizational culture) must be supported by real resource availability for successful adoption to occur.

However, while financial capacity was found to be significantly related to adoption, their influence was moderately lower than board characteristics and technological characteristics in the overall regression model. This indicates that while financial readiness is necessary, it is not sufficient on its own. Institutions must also exhibit strong governance and perceive technologies as beneficial and compatible with existing systems to realize adoption. Therefore, financial health acts as a foundational enabler rather than the primary driver of adoption. This reinforces the holistic nature of the TOE framework, where no single factor dominates but rather works in synergy with others.

Another important implication from the study is that interventions aimed at accelerating digital transformation in the SACCO sector must address financial limitations head-on. Development partners, regulators, and fintech providers could consider models such as shared digital infrastructure, subsidized onboarding for low-capacity SACCOs, or financial incentives for technology adoption. These strategies would help level the playing field and support undercapitalized institutions in keeping pace with industry transformation.

In conclusion, the findings for the first objective strongly support the TOE framework's emphasis on organizational resources, especially financial capacity, as key enablers of technological adoption. By empirically linking profitability, asset quality, and capital adequacy with the adoption of AI, blockchain, and ML, this study not only validates theoretical expectations but also addresses important empirical gaps in the literature. The evidence suggests that efforts to enhance digital innovation in Kenya's SACCO sector must take financial realities into account to be both effective and sustainable

5.3.2 Board characteristics and the Extent of Adoption of Emerging Technologies

The second objective of the study was to examine the influence of board characteristics, namely board size, board independence, and board diversity, on the adoption of emerging technologies in credit analysis by SACCOs in Kenya. The findings revealed that board characteristics had a very strong positive relationship with the extent of technology adoption, even surpassing financial capacity in the regression model. These findings are consistent with the organizational dimension of the Technology-Organization-Environment (TOE) framework, which posits that internal structures, including leadership and decision-making frameworks, are critical for technology integration (Awa et al., 2017; Rambe et al., 2022).

Within this framework, a well-structured board enhances an organization's readiness by improving strategic direction, accountability, and resource mobilization. These factors that are essential for the successful adoption of complex technologies like AI, ML, and blockchain. The study's specific focus on board-level attributes adds a novel layer to the TOE's broad organizational category. For instance, a moderately sized board (average of 8.99 members) was shown to be effective in supporting technology adoption without incurring decision-making delays that are typical of excessively large boards. This reflects existing literature suggesting that while large boards bring diverse perspectives, optimal board size facilitates more agile and coordinated decision-making processes (Chen et al., 2021; Paramesha et al., 2024)

Board independence, measured as the proportion of non-executive members, was another significant factor. The presence of independent directors introduces objective oversight, reducing managerial entrenchment and bias, thereby promoting rational and data-driven decisions around technology adoption. This finding aligns with studies by Eskandarany (2024), who noted that strategic leadership from the board is crucial in integrating AI and ML in financial institutions. However, Eskandarany's study was qualitative and did not isolate the role of board independence, a gap that this research addresses by quantifying its impact in the SACCO context.

Board diversity was also positively correlated with technology adoption. Diverse boards, comprising members with varied gender, educational, and professional backgrounds, are better positioned to evaluate emerging technologies from multiple perspectives and to advocate for inclusive innovation policies (Zeraati, 2024; Paramesha et al., 2024). This corroborates findings by Kok and Siripipatthanakul (2023), who observed that institutions with well-developed governance structures were more successful in adopting AI and ML tools, though they did not measure diversity as a standalone variable. The current study fills this empirical gap by demonstrating how diverse governance contributes to SACCOs' innovation readiness.

The consistency between these findings and the TOE framework further confirms that governance quality is not a peripheral but rather a central enabler of digital transformation. Governance structures that are inclusive, strategic, and balanced enable institutions to allocate resources wisely, manage implementation risks, and build staff confidence in new systems. These are essential prerequisites for adopting technologies that require not only capital investments but also shifts in organizational culture and workflow.

Nevertheless, the study also highlights a structural challenge: female representation on SACCO boards remains low (mean of 19.3%). While board diversity was statistically significant, the relatively limited gender diversity points to a missed opportunity for broadening innovation perspectives. This echoes concerns raised by Paramesha et al. (2024), who emphasized the transformative potential of inclusive leadership in technology adoption. Future initiatives should aim to improve gender diversity as a strategic lever for promoting inclusive innovation.

Another noteworthy observation is that board characteristics demonstrated slightly stronger predictive power than financial capacity in the regression model. This suggests that even moderately resourced SACCOs can succeed in adopting emerging technologies if they possess strong governance structures. Such a finding shifts the traditional narrative that financial strength is the primary determinant of innovation. Instead, it underscores the importance of leadership, strategic vision, and institutional alignment.

Finally, while the TOE framework accounts for organizational elements broadly, it does not explicitly address how individual board characteristics interact (such as how diversity enhances or counterbalances board independence). Future theoretical refinements or empirical models could benefit from incorporating these interactions to provide a more granular understanding of governance dynamics in technology adoption.

In conclusion, the findings for the second objective robustly support the TOE framework's organizational dimension and are consistent with the empirical literature. The study contributes uniquely by quantitatively linking specific governance indicators, including board size, independence, and diversity, to the adoption of emerging technologies in SACCOs. This not only validates existing theory but also fills critical gaps in current research, offering a more precise roadmap for policy and institutional reforms aimed at digital transformation in cooperative financial institutions

5.3.3 Technology Characteristics and the Extent of Adoption of Emerging Technologies

The third objective of the study was to examine how technological characteristics, namely perceived relative advantage, compatibility, trust, security, and complexity, influence the extent of adoption of emerging technologies in credit analysis among deposit-taking SACCOs in Kenya. Contrary to expectations and prevailing theory, the regression analysis revealed that technological characteristics did not significantly predict the extent of adoption of artificial intelligence (AI), machine learning (ML), and blockchain within the SACCO sector. This result diverges from the assumptions of the Technology-Organization-Environment (TOE) framework, which emphasizes the central role of technological features in shaping adoption decisions (Tornatzky & Fleischer, 1990; Awa et al., 2017).

According to the TOE framework, an innovation is more likely to be adopted when it offers a relative advantage over existing practices, is compatible with the organization's existing systems, is perceived as trustworthy and secure, and is not overly complex (Rambe et al., 2022). These propositions have been reinforced in prior empirical studies that suggest technological characteristics, particularly perceived usefulness, trust, and ease of use, are key drivers of adoption decisions (Bhatti, 2019; Polisetty et al., 2024; Neumann et al., 2024). However, the present study's findings challenge this narrative in the context of SACCOs in Kenya.

The lack of significance may reflect contextual and institutional realities specific to Kenyan SACCOs. While respondents generally recognized the potential benefits of emerging technologies, such as improved efficiency and fraud reduction, these perceptions did not necessarily translate into adoption. This disconnect suggests that, in practice, other factors, such as financial capacity and board characteristics, are more immediate determinants of adoption behavior. Even when a technology is perceived as advantageous or compatible, SACCOs may lack the capital, leadership direction, or implementation readiness to act on those perceptions. This supports the idea that favorable technology perceptions are necessary but not sufficient conditions for adoption.

Moreover, this result may indicate that SACCOs are not yet technologically mature enough for perceptions of innovation-specific features to matter significantly. Many SACCOs may still be in early stages of digital transformation, where structural enablers (such as financial and governance capacity) dominate decision-making. Supporting this interpretation, previous studies such as Hoque et al. (2024) and Bouteraa et al. (2024) have highlighted that in under-resourced institutions, technology-related decisions are often postponed until more fundamental capabilities are in place.

This finding also partially aligns with Jena (2022), who found that despite positive perceptions about blockchain security, actual adoption in Indian banks remained low due to regulatory and organizational readiness barriers. Similarly, Mogaji and Nguyen (2021) observed that even when AI and ML were perceived as beneficial, perceived complexity and the lack of enabling institutional environments slowed adoption, especially in developing country settings. The current study therefore contributes to a growing body of evidence suggesting that favorable perceptions alone do not guarantee technology uptake, particularly in resource-constrained financial institutions.

The absence of a significant relationship also calls into question whether SACCOs have adequate exposure or awareness of the technologies in question. If decision-makers have not directly interacted with AI, ML, or blockchain systems, their assessments of trust, compatibility, or complexity may be theoretical rather than experiential. This gap could dilute the predictive power of perceived technological characteristics. It may also reflect limited engagement with vendors or a lack of access to training and pilot programs that would otherwise help build concrete trust in these systems.

From a theoretical standpoint, these results suggest that the TOE framework may need contextual adjustment when applied to semi-formal financial institutions in developing economies. While the framework posits equal influence from technological, organizational, and environmental factors, this study shows that technological characteristics may be subordinate to board characteristics and financial capacity in determining adoption in low-resource settings. Thus, while the TOE model remains a valuable lens, its components may not carry equal weight in all contexts.

Practically, this implies that interventions aimed at boosting adoption of emerging technologies in SACCOs should not focus exclusively on communicating the benefits or technical merits of these tools. Instead, efforts should be directed at strengthening governance capacity, offering financial support for implementation, and building institutional readiness through staff training and infrastructure upgrades. Technology providers should consider bundling their solutions with support services that reduce implementation risks and complexity, especially since these concerns, though not statistically significant, still surfaced in qualitative feedback.

In conclusion, while technological characteristics are widely recognized in literature as important enablers of innovation, their influence on the extent of adoption of emerging technologies by SACCOs in Kenya was not statistically significant in this study. This suggests that structural and institutional factors, such as financial and governance readiness, play a more decisive role in the early stages of digital transformation in this sector. The findings add nuance to the TOE framework by underscoring the context-dependent nature of its constructs and highlight the need for holistic strategies that address institutional capacity as a precursor to technology-driven innovation.

5.4 Recommendations

5.4.1 Policy Recommendations

Based on the key findings of this study, several policy recommendations emerge to enhance the adoption of emerging technologies in credit analysis among deposit-taking SACCOs in Kenya.

First, given that board characteristics, especially board size, independence, and diversity, were the strongest predictors of adoption, policymakers should strengthen corporate governance frameworks within SACCOs by mandating minimum standards for board composition, encouraging gender and professional diversity, and promoting the inclusion of independent directors. Second, since financial capacity such as profitability, capital adequacy, and asset quality also had a significant influence, regulators like SASRA could consider creating financial support mechanisms, such as technology adoption grants or subsidized digital infrastructure loans, targeted at SACCOs with strong operational fundamentals. Lastly, although technological characteristics were not significant predictors, this points to a potential lack of awareness or readiness; therefore, policy interventions should prioritize capacity-building programs, including training workshops, knowledge-sharing platforms, and pilot technology trials, to improve familiarity and trust in digital tools among SACCO leadership. These combined efforts would ensure that SACCOs are both structurally and strategically equipped to integrate AI, ML, and blockchain into their credit analysis processes.

5.4.2 Managerial Recommendations

Based on the regression findings of this study, SACCO managers should prioritize enhancing internal governance structures and maintaining strong financial health to support the adoption of emerging technologies. Specifically, the significant influence of board characteristics suggests that efforts should be directed toward optimizing board composition by ensuring an appropriate size, increasing the presence of independent members, and promoting diversity in terms of gender and professional expertise. These attributes contribute to better strategic oversight and a greater openness to innovation. Additionally, the positive association between financial indicators (such as profitability, asset quality, and capital adequacy) and technology adoption underscores the importance of sound financial management. Managers should focus on improving loan performance, sustaining revenue growth, and building adequate capital buffers to create the financial flexibility needed for technological investments. While technological characteristics were not statistically significant in predicting adoption, it remains essential for managers to facilitate organizational readiness through staff training, process alignment, and gradual implementation of digital tools. Collectively, these measures will strengthen institutional capacity and support long-term digital transformation.

5.4.3 Theoretical Recommendations

The findings of this study offer important theoretical implications for the Technology-Organization-Environment (TOE) framework. While the model posits that technological, organizational, and environmental contexts collectively influence technology adoption, this study revealed that not all dimensions exert equal influence in practice. Specifically, the organizational dimension, represented by board characteristics, and the financial component of the internal environment emerged as significant predictors of adoption, whereas technological characteristics were not statistically significant. This suggests that, in resource-constrained and semi-formal financial institutions such as SACCOs, structural and institutional readiness may play a more decisive role than perceptions of technology features. Therefore, scholars applying the TOE framework in similar contexts may consider giving greater weight to governance and financial capacity within the organizational domain. Additionally, future theoretical extensions of TOE could integrate more nuanced constructs, such as board composition and capital adequacy, to enhance explanatory power in settings where institutional structure heavily mediates innovation decisions. This context-sensitive interpretation underscores the need to adapt broad theoretical models to the unique realities of specific sectors and regions.

5.5 Limitations of the Study

This study has several methodological and conceptual limitations. Methodologically, the reliance on cross-sectional data limits the ability to establish causal relationships or observe how technology adoption evolves over time. The use of primary surveys for technology characteristics and extent of adoption may introduce self-reporting biases, while the secondary data from annual reports for financial and board characteristics may not fully capture nuanced organizational dynamics. The study's focus on Kenyan SACCOs also limits generalizability to other financial institutions or geographic contexts. Additionally, the operationalization of technology characteristics as perceptual measures rather than objective assessments of technological readiness may have affected the robustness of these findings. Additionally, the study did not examine potential interaction effects between different categories of predictors, which might reveal more complex adoption pathways.

5.6 Contribution to Knowledge

This study makes several contributions to the existing body of knowledge on the adoption of emerging technologies—specifically artificial intelligence (AI), blockchain, and machine learning (ML), within the context of credit analysis in deposit-taking SACCOs (DTSs) in Kenya.

First, the study addresses a contextual gap by focusing on SACCOs, which have been largely overlooked in previous research that has concentrated on commercial banks and fintech institutions. SACCOs play a vital role in financial inclusion in Kenya, yet their capacity and readiness to adopt emerging technologies remain underexplored. This study therefore contributes new insights specific to resource-constrained cooperative institutions, making the findings more relevant for policymakers and practitioners working within this subsector.

Second, the study extends the application of the Technology-Organization-Environment (TOE) framework by empirically testing the influence of financial characteristics and governance structures alongside perceived technology attributes. The results revealed that organizational factors, particularly financial strength and board characteristics, are more predictive of adoption than technology characteristics alone. This offers a refined understanding of the TOE model, especially in low-resource environments, and suggests the need to emphasize organizational readiness in future applications of the model.

Third, the study contributes methodologically by integrating both primary (questionnaire-based) and secondary (financial and governance data from annual reports) sources. This dual-source approach strengthens the validity of the findings and demonstrates a robust method for examining technology adoption in institutions where subjective perceptions and objective conditions both play a role.

Finally, the study offers empirical clarity by quantifying specific indicators—such as profitability, asset quality, board independence, and perceived complexity—thereby operationalizing constructs that have often been treated in abstract or qualitative terms in previous literature. This enhances the replicability and comparability of future research in this area.

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5.7 Suggestions for Further Research

Future research should address the limitations of this study through longitudinal designs to capture the dynamic nature of technology adoption and its long-term impacts on SACCO performance. Mixed-method approaches combining surveys with in-depth interviews could provide richer insights into the contextual factors influencing adoption decisions, particularly the role of individual-level determinants like staff technological proficiency and leadership commitment. Comparative studies across different types of financial institutions (e.g., commercial banks, microfinance) and regions would enhance the generalizability of findings, while also exploring how environmental factors like regulatory frameworks and competitive pressures interact with organizational characteristics. Future work could also test expanded theoretical models that integrate additional dimensions such as user acceptance (such as the Technology Acceptance Model) or institutional pressures (such as the Institutional Theory) alongside the TOE framework. Finally, research could explore the implementation challenges and success factors post-adoption, including how SACCOs leverage these technologies to improve credit risk assessment and operational efficiency in practice.

5.8 Chapter Summary

This chapter has summarized and discussed the findings. This study found that financial strength and board characteristics were the strongest predictors of emerging technology adoption in Kenyan SACCOs while technology characteristics showed weaker influence. The findings validate the TOE framework's organizational dimension but suggest that resource-constrained institutions prioritize financial capacity and board characteristics over technological features when adopting innovations. Practically, this implies that interventions to accelerate digital transformation should first strengthen SACCOs' financial health and board characteristics before addressing technological perceptions.

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APPENDICES

Appendix I: Letter of Introduction

You are being invited to take part in a research study titled, “Determinants of Adoption of Emerging Technologies in Credit Analysis: A Study of Deposit-Taking Saccos in Kenya.” This research is being conducted by Ja’afar Aden, a student at Strathmore Business School. You may contact the researcher via email at Jaafar.kosar@strathmore.edu or phone at +254 725 606 212.

The aim of this study is to examine the extent of adoption of emerging technologies, specifically artificial intelligence (AI), blockchain, and machine learning (ML), in credit analysis by deposit-taking SACCOs in Kenya. The study seeks to explore organizational factors and management perspectives that influence the adoption of these technologies. Your participation will provide valuable insights into how these technologies are utilized in credit risk management and contribute to enhancing the operational efficiency of SACCOs.

If you agree to participate, you will be asked to complete a questionnaire, which will take approximately 15-20 minutes. The questionnaire will gather information regarding your experiences and perceptions related to the adoption and implementation of AI, blockchain, and ML in credit analysis. Participation in this study is entirely voluntary, and you may choose not to answer any question or withdraw from the study at any time without any negative consequences.

Please note that your responses will remain confidential, and no personal information will be shared publicly. The findings will only be used for academic purposes.

If you have any questions or need further clarification regarding the research, please feel free to contact Ja’afar Aden at +254 725 606 212 or via email at Jaafar.kosar@strathmore.edu.

Thank you for considering participating in this study. Your input is highly appreciated and will contribute significantly to this research.

Sincerely,

Ja’afar Aden

Strathmore Business School

Appendix II: Participant Information and Informed Consent

PARTICIPANT INFORMATION AND CONSENT FORM

INSERT HEADING FOR THE PROPOSED STUDY

DETERMINANTS OF THE EXTENT OF ADOPTION OF EMERGING TECHNOLOGIES IN CREDIT ANALYIS: A STUDY OF DEPOSIT-TAKING SACCOS IN KENYA

SECTION 1: INFORMATION SHEET

Investigator: Ja'afar Aden

Institutional affiliation: Strathmore Business School (SBS)

SECTION 2: INFORMATION SHEET–THE STUDY

2.1 : Why is this study being carried out?

The main objective of this research is to examine the factors influencing the adoption of emerging technologies, including artificial intelligence, block chain, and machine learning, in credit analysis among DTSs in Kenya. The specific objectives will be to determine the influence of financial factors, governance characteristics and technology characteristics, on the extent of adoption of emerging technologies in credit analysis by deposit-taking SACCOs in Kenya.

2.2 : Do I have to take part?

No. Taking part in this study is entirely optional and the decision rests only with you. If you decide to take part, you will be asked to complete a questionnaire to get information on your demographic details, such as age, gender, and work experience. You will also provide information related to your demographic characteristics, and how your SACCO perceives emerging technologies in relation to credit analysis. If you are not able to answer all the questions successfully the first time, you may be asked to sit through another informational session after which you may be asked to answer the questions a second time. You are free to decline to take part in the study from this study at any time without giving any reasons.

2.3 : Who is eligible to take part in this study?

- Managers of deposit-taking SACCOs in Kenya
- Those aged 18+ years
- Those who do not have any cognitive impairments

2.4 : Who is not eligible to take part in this study?

- Those who have cognitive impairments
- Those who are below the age of 18 years

2.5 : What will taking part in this study involve for me?

You will be approached by Ja'afar Aden and requested to take part in the study. If you are satisfied that you fully understand the goals behind this study, you will be asked to sign the informed consent form (this form) and then taken through a questionnaire to complete.

2.6 : Are there any risks or dangers in taking part in this study?

There are no risks in taking part in this study. All the information you provide will be treated as confidential and will not be used in any way without your express permission.

2.7 : Are there any benefits of taking part in this study?

The information will contribute to a better understanding of the determinants of adoption of emerging technologies by deposit-taking SACCOs. The insights from this study will be useful in encouraging adoption

2.8 : What will happen to me if I refuse to take part in this study?

Participation in this study is entirely voluntary. Even if you decide to take part at first but later change your mind, you are free to withdraw at any time without explanation.

2.9 : Who will have access to my information during this research?

All research records will be stored in securely locked cabinets. That information may be transcribed into our database but this will be sufficiently encrypted and password protected. Only the people who are closely concerned with this study will have access to your information. All your information will be kept confidential.

2.10 : Who can I contact in case I have further questions?

You can contact me, Ja'afar Aden, at SBS, or by e-mail (jaafar.kosar@strathmore.edu), or by phone (+254 725 606 212). You can also contact my supervisor, Dr. Geoffrey Injeni, at the Strathmore Business School, Nairobi, or by e-mail (ginjeni@strathmore.edu) or by phone (+254 722 292 195)

If you want to ask someone independent anything about this research please contact:

The Secretary–Strathmore University Institutional Ethics Review Board, P. O. BOX 59857, 00200, Nairobi, email ethicsreview@strathmore.edu Tel number: +254 703 034418

I, ______________________________, have had the study explained to me. I have understood all that I have read and have had explained to me and had my questions answered satisfactorily. I understand that I can change my mind at any stage.

Please tick the boxes that apply to you;

Participation in the research study

☐ I AGREE to take part in this research

☐ DON'T AGREE to take part in this research

Storage of information on the completed questionnaire

☐ I AGREE to have my completed questionnaire stored for future data analysis

☐ DON'T AGREE to have my completed questionnaire stored for future data analysis

Participant's Signature: ______________________________ **Date:** _____/______/.

DD / MM / YEAR

Participant's Name: ______________________________ **Time:** _____/_______

(Please print name) ***HR / MN***

I, ______________________(Name of person taking consent) certify that I have followed the SOP for this study and have explained the study information to the study participant named above, and that s/he has understood the nature and the purpose of the study and consents to the participation in the study. S/he has been given opportunity to ask questions which have been answered satisfactorily.

Investigator's Signature: ______________________________ **Date:** _____/______/.

DD / MM / YEAR

Investigator's Name: ______________________________ **Time:** _____/_______

(Please print name) ***HR / MN***

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Appendix III: Ethical Approval and NACOSTI License

Strathmore UNIVERSITY

14th April 2025

Mr Kosar Ja'afar,
Jaafar.Kosar@strathmore.edu

Dear Mr Kosar,

RE: Determinants of the Extent of Adoption of Emerging Technologies in Credit Analysis: A Study of Deposit-Taking SACCOs in Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2891/25.** The approval period is from **14th April 2025 to 13th April 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, 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 affected 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

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

National Commission for Science, Technology and Innovation -

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **732841**

Date of Issue: **14/April/2025**

RESEARCH LICENSE

This is to Certify that Mr.. Ja'afar Aden Kosar of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kericho, Kiambu, Kisumu, Mombasa, Nairobi, Nakuru, Nyeri, Uasin-Gishu on the topic: DETERMINANTS OF THE EXTENT OF ADOPTION OF EMERGING TECHNOLOGIES IN CREDIT ANALYSIS: A STUDY OF DEPOSIT-TAKING SACCOS IN KENYA for the period ending : 14/April/2026.

License No: **NACOSTI/P/25/4172543**

732841

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY &
INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document,
Scan the QR Code using QR scanner application.

See overleaf for conditions

Appendix IV: Questionnaire

Section A: Demographic Profile

Please provide the following information by ticking (√) the appropriate box or filling in the required details.

1. Gender
☐ Male
☐ Female

2. Age
☐ 18-24
☐ 25-34
☐ 35-44
☐ 45-54
☐ 55 and above

3. Highest level of education completed
☐ Certificate/Diploma
☐ Undergraduate degree
☐ Postgraduate degree

4. Position in the SACCO
☐ Manager
☐ Assistant Manager
☐ Credit Officer
☐ Operations Officer
☐ Other (Please specify): ____________

5. Number of years worked in the SACCO
☐ Less than 1 year
☐ 1-3 years
☐ 4-6 years
☐ 7-10 years
☐ More than 10 years

6. Sector of SACCO (Please tick one)
☐ Agricultural
☐ Transport
☐ Housing
☐ Financial

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☐ Other (Please specify): ___________

7. Size of the SACCO (Based on total membership)
☐ Less than 500 members
☐ 500-1000 members
☐ 1001-5000 members
☐ More than 5000 members

8. Annual Turnover of the SACCO
☐ Less than Ksh 50 million
☐ Ksh 50 million - Ksh 100 million
☐ Ksh 100 million - Ksh 500 million
☐ More than Ksh 500 million

Section B: Technology Characteristics

For each of the following statements, please indicate the extent to which you agree or disagree by selecting one of the options below. Use the scale provided where:
1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree

Please answer each question based on how senior management perceive the characteristics of emerging technologies (artificial intelligence, machine learning, and blockchain) in credit analysis.

Relative Advantage

1. Senior management believes that the adoption of artificial intelligence (AI) will significantly improve credit analysis processes.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
2. Senior management perceives machine learning (ML) as a tool that will provide a competitive advantage in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3. The use of blockchain technology is seen by senior management as beneficial for enhancing transparency and security in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Trust

1. Senior management has a high level of trust in the ability of artificial intelligence (AI) to accurately assess credit risk.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
2. Senior management believes that machine learning (ML) algorithms can be trusted to make reliable credit decisions.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3. Senior management feels confident in the security and reliability of blockchain for preventing fraud in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Compatibility

1. Senior management believes that artificial intelligence (AI) is compatible with the existing credit analysis processes in the SACCO.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
2. The use of machine learning (ML) is seen as compatible with the SACCO's current technological infrastructure and systems.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3. Senior management perceives blockchain technology as compatible with the SACCO's operational processes in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Security

1. Senior management believes that artificial intelligence (AI) tools used in credit analysis provide sufficient data protection.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
2. Senior management considers machine learning (ML) algorithms to be secure in handling sensitive customer data in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3. Senior management views blockchain technology as providing a highly secure method for storing and verifying credit-related transactions.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Complexity

1. Senior management believes that the implementation of artificial intelligence (AI) for credit analysis is complex and requires substantial effort to integrate.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

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2. Senior management considers machine learning (ML) to be a complex technology that is challenging to adopt in credit analysis.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
3. Senior management perceives blockchain technology as complex, making it difficult to implement in the SACCO's credit analysis processes.
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section C: Extent of Adoption of Emerging Technologies

For each of the following statements, please indicate the extent to which you agree or disagree by selecting one of the options below. Use the scale provided where:
1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree

Please answer each question honestly based on your experience and knowledge of your SACCO.

Artificial Intelligence

1. The SACCO uses AI tools to analyze member creditworthiness and make lending decisions.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. AI systems are used in the SACCO to predict loan defaults and manage credit risk.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. The SACCO employs AI-powered chatbots to provide real-time customer support.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. Fraud detection in the SACCO is enhanced through AI-based monitoring systems.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5.AI tools are used in the SACCO to automate routine tasks like loan application processing.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Machine Learning

1. Machine learning models are used in the SACCO to identify patterns in member savings and borrowing behavior.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

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2. The SACCO uses machine learning algorithms to optimize loan approval processes.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Predictive analytics powered by machine learning is used in the SACCO for financial forecasting.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. Machine learning helps the SACCO personalize financial products based on members' past transactions.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5. Member retention strategies in the SACCO are guided by insights generated from machine learning models.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Blockchain

1. The SACCO uses blockchain to maintain secure and tamper-proof transaction records.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. Blockchain technology is applied in the SACCO to automate loan agreements through smart contracts.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Digital identities based on blockchain are used in the SACCO to streamline member verification processes.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. Blockchain systems in the SACCO enhance transparency and build member trust.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5. The use of blockchain has improved the speed and accuracy of financial transactions in the SACCO.
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Thank You

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Appendix V: List of Deposit-Taking SACCOs in Kenya

1	2NK Sacco Society Ltd	P.O Box 12196 – 10109, Nyeri	Kangaru Building, Gakere Road	Nyeri
2	Acumen DT Sacco Society Limited	P.O. Box 1325 – 00200, Kajiado	Great Wide Mall, Magadi Road, Rongai	Kajiado
3	Afya Sacco Society Ltd	P.O Box 11607 – 00400, Nairobi.	Afya Centre, Tom Mboya Street, Nairobi	Nairobi
4	Agrochem Sacco Society Ltd	P.O Box 94 – 40107 Muhoroni	Muhoroni Town	Kisumu
5	Ainabkoi Sacco Society Ltd	P.O Box 120-30101, Ainabkoi	Ainabkoi Farmers' Cooperative Society Land Eldoret, Naiberi, Timboroa Road	Uasin Gishu
6	Airports Sacco Society Ltd	P.O Box 19048 – 00500, Nairobi	Kenya Airports Authority Head Quarters Building	Nairobi
7	Amica Sacco Society Ltd	P.O Box 816 – 10200, Murang'a	Mugama Union Building – Uhuru Road, Murang'a	Murang'a
8	Ammar Sacco Society Ltd	P.O Box 6957 – 01000, Thika	Elica Plaza, Kwame Nkrumah Road, Thika Town	Murang'a
9	Apstar DT Sacco Society Ltd	P.O Box 44071 – 00100, Nairobi	Ukulima Cooperative House, Haile Selassie Avenue, Nairobi	Nairobi
10	Ardhi Sacco Society Ltd	P.O Box 28782 – 00200, Nairobi	Survey Kenya Field Headquarters, Off Thika Road	Nairobi
11	Asili Sacco Society Ltd	P.O Box 49064 – 00100 Nairobi	Asili Co–op Centre, The Lower Ngara Road, Nairobi	Nairobi
12	Azima Sacco Society Ltd	P.O Box 1124 – 01000, Thika	Azima Sacco Plaza, Wabera Street, Thika	Kiambu
13	Bandari Sacco Society Ltd	P.O Box 95011 – 80104, Mombasa	Moi Avenue, Mombasa	Mombasa
14	Baraka Sacco Society Ltd	P.O Box 1548 – 10101, Karatina	Station Road, Off Kiaruhiu Street, Karatina	Nyeri
15	Baraton Sacco Society Ltd	P.O Box 2500 – 30100, Eldoret	University Of Eastern Africa, Baraton, Off Eldoret – Kapsabet Road, Chepterit Junction	Nandi
16	Bi – High Sacco Society Ltd	P.O. Box 90 – 60500, Marsabit	Marsabit Teachers Plaza,Mosque Road,Marsabit	Marsabit
17	Biashara Sacco Society Ltd	P.O Box 1895 – 10100 Nyeri	Biashara Sacco Building, Kimathi Way, Nyeri Town	Nyeri
18	Biashara Tosha Sacco Society Ltd	P.O. Box 189 – 60101, Embu	Gakundu F.C.S Building, Embu – Kianjokoma Road, Embu	Embu
19	Bingwa Sacco Society Ltd	P.O Box 434 – 10300, Kerugoya	Bingwa Sacco Complex, Kutus – Karatina Road, Kerugoya Town	Kirinyaga
20	Boresha Sacco Society Ltd	P.O Box 80 – 20103, Eldama Ravine	Teachers Plaza – Market Road, Eldama Ravine Town	Baringo
21	Capital Sacco Society Ltd	P.O Box 1479 – 60200, Meru	Maccu Building, Kenyatta Highway, Meru	Meru
22	Centenary Sacco Society Ltd	P.O Box 1207 – 60200, Meru	Intercity Building, Meru – Nanyuki Highway, Meru Town Centre	Meru
23	Chai Sacco Society Ltd	P.O Box 278 – 00200, Nairobi	Chai House, Koinange Street, Nairobi	Nairobi
24	Chuka University Sacco Society Ltd	P.O Box 109 – 60400, Chuka	Chuka University, Students Recreation Centre, Chuka Town	Tharaka Nithi
25	Chuna Sacco Society Ltd	P.O Box 30197 – 00100, Nairobi	University of Nairobi, Engineering Department Building – Harry Thuku Road	Nairobi

26	Cosmopolitan Sacco Society Ltd	P.O Box 1931 – 20100 Nakuru	Natec Plaza, Kijabe Row Street, Nakuru	Nakuru
27	County Sacco Society Ltd	P.O Box 21 – 60103, Runyenjes	County Sacco Building, Kanja Shauri Road, Kanja Town	Embu
28	Daima Sacco Society Ltd	P.O Box 2032 – 60100, Embu	Daima Sacco Building, Mutunduri – Kianjokoma Road, Manyatta Market Centre	Embu
29	Defence Sacco Society Ltd	P.O Box 40668 – 00100 Nairobi	Ulinzi House, Lenana Road, Hurlingham, Nairobi	Nairobi
30	Dhabiti Sacco Society Ltd	P.O Box 353 – 60600, Maua	Dhabiti Sacco Building, Maua – Mikinduri Road, Maua Township	Meru
31	Dimkes DT Sacco Society Ltd	P.O Box 886 – 00900, Kiambu	Bishop Magua House, Biashara Street, Kiambu Town	Kiambu
32	Dumisha Sacco Society Ltd	P.O. Box 84 – 20600 Maralal	Dumisha Sacco Plaza - Harambee Road, Maralal	Samburu
33	Eco – Pillar Sacco Society Ltd	P.O Box 48 – 30600 Kapenguria	Makutano Teachers Plaza, Lotodo Street, Kapenguria Town	West Pokot
34	Edis Sacco Society Ltd	P.O. Box 228 – 20400, Bomet	Ngocho Building, Opposite NCPD, Ngocho, Bomet	Bomet
35	Egerton University Sacco Society Ltd	P.O Box 178 – 20115 Egerton	Egerton Sacco Plaza, Egerton University, Njoro Township	Nakuru
36	Elimu Sacco Society Ltd	P.O Box10073 – 00100, Nairobi	Mubiru Road, Nairobi	Nairobi
37	Enea Sacco Society Ltd	P.O Box 1836 – 10101 Karatina	Kiangararu House, Karatina – Nairobi Highway, Karatina Town	Nyeri
38	Faridi Sacco Society Ltd	P.O Box 448 – 50400, Busia	Faridi Housing Plaza, Busia – Kisumu Road	Busia
39	Fariji Sacco Society Ltd	P.O. Box 589 – 00216, Githunguri	Diplomat Building, Githunguri Street, Kiambu	Kiambu
40	Fortitude Sacco Society Ltd	P.O Box 237 – 40205, Mbita	Fortitude Sacco Building, Mbita Township	Homabay
41	Fortune Sacco Society Ltd	P.O. Box 559 – 10300, Kerugoya	Fortune Plaza, Main Street, Kerugoya	Kirinyaga
42	Fundilima Sacco Society Ltd	P.O. Box 62000 – 00200 Nairobi	Fedha House,JKUAT, Juja Town	Kiambu
43	GDC Sacco Society Ltd	P.O. Box 896 – 00216, Githunguri	GDC Sacco Plaza, Market Street, Kiambu	Kiambu
44	Golden Pillar Sacco Society Ltd	P.O Box 3192 – 60200, Meru	Imenti Complex, Main Stage, Meru Town	Meru
45	Good Faith Sacco Society Ltd	P.O. Box 224 – 00222, Uplands	Nyambari Kiambu – Kiwa House, Uplands Githunguri Road	Kiambu
46	Goodway Sacco Society Ltd	P.O Box 662 – 10300, Kerugoya	Machere Plaza, Kerugoya Back Street, Kerugoya Town	Kirinyaga
47	Gusii Mwalimu Sacco Society Ltd	P.O Box 1335 – 40200, Kisii	Mwalimu House, Kisii – Kericho Road, Kisii	Kisii
48	Harambee DT Sacco Society Ltd	P.O Box 47815 – 00100, Nairobi	Harambee Sacco Plaza, Haile Selassie Avenue, Nairobi	Nairobi
49	Hazina Sacco Society Ltd	P.O Box 59877 – 00200, Nairobi	Hazina Sacco Place, Ngong Road, Nairobi	Nairobi

50	Home Business Sacco Society Ltd	P.O Box 1073 – 20300,Nyahururu	Tec Biz Centre, Koinange Road, Nyahururu Town	Laikipia
51	Ilkisonko Sacco Society	P.O Box 91 – 00209, Loitokitok	Musangairo FCS Building, Loitokitok Town	Kajiado
52	Imarika Sacco Society Ltd	P.O Box 712 – 80108, Kilifi	Imarika Plaza, Kenyatta Road, Kilifi	Kilifi
53	Imarisha Sacco Society Ltd	P.O. Box 682 – 20200, Kericho	Kipsigis Teachers Cooperative House, Kisumu – Nakuru Highway	Kericho
54	Invest & Grow (IG) Sacco Society Ltd	P.O. Box 1150 – 50100, Kakamega	Invest & Grow Plaza, Khalisia Road 3, Kakamega	Kakamega
55	Jamii Sacco Society Ltd	P.O. Box 57929 – 00200, Nairobi	Jamii Sacco Court, Mukenia Road, South B, Nairobi	Nairobi
56	Jamii Yetu Sacco Society Ltd	P.O Box 469 – 60600, Maua	Amwathi MMH Sacco Plaza, Kanuni Road, Maua	Meru
57	Jitegemee Sacco Society Ltd	P.O Box 86937 – 80100, Mombasa	L.R No. 242, Msa/Block 134/XXVI, Kizingo House No.2, Kaunda Street, Mvita, Mombasa.	Mombasa
58	Jogoo Sacco Society Ltd	P.O Box 56074 - 00200, Nairobi	Commodore Office Suites, Off Ngong/Ring Road Kindaru-ma Avenue, Nairobi	Nairobi
59	Joinas Sacco Society Ltd	P.O Box 669 – 00219 Karuri	Kanja House, Limuru – Banana Road, Banana Town	Kiambu
60	Jumuika Sacco Society Ltd	P.O BOX 14 – 40112, Awasi	Chemelil Sugar Sports Complex	Kisumu
61	K – Pillar Sacco Society Ltd	P.O Box 83 – 20403, Mogogosiek	K – Pillar Building, Bomet – Litein Road, Mogogosiek	Bomet
62	K – Unity Sacco Society Ltd	P.O Box 268 – 00900, Kiambu	K – Unity Building, Kiambu Town	Kiambu
63	Kabiyet Sacco Society Ltd	P.O. Box 195 – 30303, Kabiyet	Mosoriot – Kaiboi Road, Kabiyet Trading Centre	Nandi
64	Kencream Sacco Society Ltd	P.O Box 30131 – 00100, Nairobi	Creamary House, Dakar Road, Nairobi	Nairobi
65	Kenpipe Sacco Society Ltd	P.O Box 314 – 00507, Nairobi	Kenpipe Plaza, Sekoni Road, Nairobi	Nairobi
66	Kenversity Sacco Society Ltd	P.O Box 10263 – 00100, Nairobi	Kenversity Plaza, Kahawa Sukari Road, Nairobi	Nairobi
67	Kenya Achievas Sacco Society Ltd	P.O Box 3080 – 40200, Kisii	Achievas Plaza, Kisii – Kilgoris Road, Nyamache Town, Kisii	Kisii
68	Kenya Highlands Sacco Society Ltd	P.O Box 2085 – 20200, Kericho	Temiik House, Kericho – Kisumu Highway	Kericho
69	Kenya National Police DT Sacco Society Ltd	P.O Box 51042 – 00200, Nairobi	Kenya Police Sacco Plaza, Ngara Road, Nairobi	Nairobi
70	Keystone DT Sacco Society Ltd	P.O. Box 2073 – 40100, Kisumu	Kenya Re – Insurance Plaza, Bank Street, Kisumu	Kisumu
71	Kimbilio Daima Sacco Society Ltd	P.O Box 81 – 20225, Kericho	Chepsol Plaza, Kimulot Road, Kapset	Bomet
72	Kimisitu Sacco Society Ltd	P.O. Box 10454–00200, Nbi	AEA Plaza, Valley Road, Nairobi	Nairobi
73	Kingdom Sacco Society Ltd	P.O Box 8017 – 00300, Nairobi	Empower House, Githurai 45, Thika Road	Kiambu

74	Kolenge Tea Sacco Society Ltd	P.O Box 291 – 30301, Nandi Hills	Nandi Hills Plaza, Nandi Hills Town	Nandi
75	Koru DT Sacco Society Ltd	P.O Box Private Bag–40100, Koru	Homalime Company Limited, Koru Town	Kisumu
76	Kwetu DT Sacco Society Ltd	P.O Box 818 – 90100, Machakos	Mwalimu Centre, Syokimau Road, Machakos Town	Machakos
77	Kwikas DT Sacco Society Ltd	P.O Box 27 – 20306, Ndaragwa	Ndaragwa Umoja Building, Kimathi Road, Nyandarua	Nyandarua
78	Lainisha Sacco Society Ltd	P.O Box 272 – 10303, Wang'uru	Lainisha Sacco Building, Mwea Town, Kirinyaga	Kirinyaga
79	Lamu Teachers Sacco Ltd	P.O Box 14 – 40112, Lamu	L.R No 784/1, Lamu Teachers Sacco Building, Galogalo Street, Lamu	Lamu
80	Lengo Sacco Society Ltd	P.O. Box 1005 – 80200, Malindi	Standard Arcade – Mama Ngina Street, Malindi Town	Kilifi
81	Mafanikio Sacco Society Ltd	P.O Box 86515–80100,Mombasa	Mombasa Teachers Building, Jomo Kenyatta Avenue, Mombasa	Mombasa
82	Magadi Sacco Society Ltd	P.O. Box 13 – 00205, Magadi	Pam View Building, Magadi Road, Magadi Soda, Kajiado	Kajiado
83	Magereza Sacco Society Ltd	P.O. Box 53131 – 00200, Nairobi	Mageso Chambers, Moi Avenue, Nairobi	Nairobi
84	Maisha Bora Sacco Society Ltd	P.O. Box 30062 – 00200, Nairobi	Commercial Street, Industrial Area, Nairobi	Nairobi
85	Mentor Sacco Society Ltd	P.O Box 789 – 10200, Murang'a	Mentor Plaza, Uhuru Road, Murang'a	Murang'a
86	Metropolitan National Sacco Society Ltd	P.O Box 871¬ – 00900, Kiambu	Metropolitan National Sacco Society Ltd Building, Biashara Street, Kiambu Town	Kiambu
87	Mhasibu DT Sacco Society Ltd	P.O Box 31295 - 00600, Nairobi	Absa Towers, Market Street, Nairobi	Nairobi
88	Mudete Sacco Society Ltd.	P.O. Box 221 – 50104, Kakamega	Sacco Plaza, Khayega, Kakamega	Kakamega
89	Muki Sacco Society Ltd	P.O Box 398 – 20318, North Kinangop	Muki House, Ndunyu Njeru Road, Kinangop	Nyandarua
90	Mwalimu National Sacco Society Ltd	P.O. Box 62641 – 00200, Nairobi	Hill Lane, Nairobi City	Nairobi
91	Mwietheri Sacco Society Ltd	P.O Box 2445 – 60100, Embu	Rungeto F.C.S, Githure	Embu
92	Mwito Sacco Society Ltd	P.O Box 56763 – 00200, Nairobi	Mwito Building, Desai Road, Nairobi	Nairobi
93	Nacico Sacco Society Ltd	P.O Box 34525 – 00100, Nairobi	NACICO Plaza, Landhies Road, Nairobi	Nairobi
94	Nafasi DT Sacco Society Ltd	P.O. Box 41426 – 00100 Nairobi	NCPB Nairobi Silos Complex, Off Outering Road, Nairobi	Nairobi
95	Nandi Farmers Sacco Society Ltd	P.O Box 333 – 30301, Nandi Hills	Nandi Hills Plaza, Market Street,	Nandi
96	Nation DT Sacco Society Ltd	P.O. Box 22022 – 00400, Nairobi	Cambrian Building, Moi Avenue, Nairobi	Nairobi
97	Nawiri Sacco Society Ltd	P.O Box 400 – 60100, Embu	EMCO House, Taifa Road, Embu	Embu
98	Ndege Chai Sacco Society Ltd	P.O Box 857 – 20200, Kericho	Ndege Chai House, Kericho – Nakuru Highway, Kericho	Kericho
99	Ndosha Sacco Society Ltd	P.O. Box 532 – 60401, Tharaka Nithi	L.R No. Plot 1206, Ndosha Sacco Plaza, Chogoria.	Tharaka Nithi
100	New Fortis Sacco Society Ltd	P.O Box 1939 – 10100, Nyeri	New Fortis Sacco Plaza, Off Kenyatta Road, Nyeri Town	Nyeri
101	Nexus Sacco Society Ltd	P.O. Box 251 – 60202, Nkubu	Kathera House, Kamunara, Nkubu, Meru	Meru
102	Ng'arisha Sacco Society Ltd	P.O. Box 1199 – 50200, Bungoma	Bungoma Teachers Plaza, Bungoma	Bungoma
103	Njiwa Sacco Sacco Ltd	P.O Box 10221 – 00100, Nairobi	Golf View Office Suites, Wambui Road, Nairobi	Nairobi
104	NRS Sacco Society Ltd	P.O Box 575 – 00902, Kikuyu	Ondiri Building, Kikuyu Road, Kikuyu	Kiambu
105	NSSF Sacco Society Ltd	P.O Box 43338 – 00100, Nairobi	Social Security House, Bishops Road, Nairobi	Nairobi
106	Nufaika Sacco Society Ltd	P.O Box 735 – 10300, Kerugoya	Machere Building, Machere Street, Kerugoya Town, Kirinyaga	Kirinyaga
107	Nyambene Arimi Sacco Society Ltd	P.O Box 493 – 60600, Maua	Nyambene Arimi Sacco Plaza, Maua Kanuni Road, Meru Town	Meru

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108	Nyati Sacco Society Ltd	P.O Box 7601 – 00200, Nairobi	Odyssey Plaza, Mukoma Road, Nairobi	Nairobi
109	Ollin Sacco Society Ltd	P.O Box 83 – 10300, Kerugoya	Ollin Sacco Building, Off Karatina – Kutus Road, Kerugoya	Kirinyaga
110	Orient Sacco Society Ltd	P.O Box 1842 – 0100, Thika	Wakibe Building, Thika Section 9 OAU Road, Thika Town	Kiambu
111	Patnas Sacco Society Ltd.	P.O. Box 601 – 20210, Litein	Litein Town, Patnas Plaza, Kericho Sotik Road	Kericho
112	Ports DT Sacco Society Ltd	P.OBox 95372–80104,Mombasa	Mombasa Port Sacco Plaza, Mwakilingo Road	Mombasa
113	Prime – Time Sacco Society Ltd	P.O Box 512 – 30700, Iten	Mwalimu Plaza Building, Eldoret – Kabarnet Road, Iten	Elgeyo – Marakwet
114	Puan Sacco Society Ltd	P.O Box 404 – 20500, Narok	Farmers Building, Narok – Nakuru Road, Narok Town	Narok
115	Qona Sacco Society Ltd	P.O Box 6682 – 00800, Nairobi	Safaricom Care Centre, Waiyaki Way, Westlands, Nairobi	Nairobi
116	Qwetu Sacco Society Ltd	P.O Box 1186 – 80304, Voi	Qwetu Sacco Plaza, Voi Town	Taita Taveta
117	Sheria Sacco Society Ltd	P.O. Box 34390 – 00100, Nairobi	Matumbato Close, Nairobi	Nairobi
118	Shirika DT Sacco Society Ltd	P.O Box 43429 – 00100, Nairobi	Shirika Coop House, Ngara Kipande Road, Ngara, Nairobi	Nairobi
119	Shoppers Sacco Society Ltd	P.O BOX 16-00507, Nairobi	Nature House – Tom Mboya Street	Nairobi
120	Simba Chai Sacco Society Ltd	P.O. Box 977 – 20200, Kericho	Kericho Nakuru Highway, Kericho	Kericho
121	Siraji Sacco Society Ltd	P.O Box Private Bag	Siraji Sacco Plaza, Nanyuki – Meru Highway, Timau Town	Meru
122	Skyline DT Sacco Society Ltd	P.O Box 660 – 20103, Eldama Ravine	Skyrise Plaza, Eldama Ravine – Eldoret Road, Eldama Ravine	Baringo
123	Smart Champions Sacco Society	P.O Box 64 – 60205, Githongo	Muranene Building, Githongo Trading Centre, Meru	Meru
124	Smartlife Sacco Society Ltd	P.O Box 118 – 30705, Kapsowar	Marakwet Teachers Plaza, Kapsowar	Elgeyo – Marakwet
125	Solution Sacco Society Ltd	P.O. Box 1694 – 60200, Meru Central	Meru Mwalimu Plaza, Gakoromone Road, Meru	Meru
126	Sotico Sacco Society Ltd	P.O. Box 959 – 20406, Sotik	Amotek Estate, Sotik Town	Bomet
127	Southern Star Sacco Society Ltd	P.O Box 514 – 60400, Chuka	Mt Building, Chuka Town	Tharaka Nithi
128	Stake Kenya Sacco Society Ltd	P.O Box 208 – 40413, Kehancha	Stake Kenya Sacco Plaza, Migori – Kehancha – Ntimaru Road, Kehancha	Migori
129	Stawisha Sacco Society Ltd	P.O Box 27 – 50203, Kapsok-wony	Mwalimu Plaza, Kapsokwony – Kaptama Road, Kapsok-wony	Bungoma
130	Stima DT Sacco Society Ltd	P.O Box 75629 – 00200, Nairobi	Stima Sacco Plaza, Mushembi Road, Parklands, Nairobi	Nairobi
131	Strategic DT Sacco Society Ltd.	P.O. Box 78506 – 00507, Nairobi	Lunga Lunga Square, Industrial Area, Nairobi County.	Nairobi

132	Suluhu Sacco Society Ltd	P.O Box 489 – 90400, Mwingi	Suluhu Sacco Plaza, Kyuso Road, Mwingi	Kitui
133	Supa Sacco Society Ltd	P.O. Box 271 – 20600, Maralal	Supa Plaza, Posta Road, Maralal	Samburu
134	Tabasamu Sacco Society Ltd	P.O Box 123 – 80403, Kwale	Tunawiri House, Kinango Road, Kwale	Kwale
135	Tabasuri DT Sacco Society Ltd	P.O Box 80862 – 80100, Mombasa	Texas Plaza, Off Fidel Odinga Road, Mombasa	Mombasa
136	Tai Sacco Society Ltd	P.O Box 718 – 00216, Githunguri	Tai Plaza, Githunguri Town, Kiambu	Kiambu
137	Taifa Sacco Society Ltd	P.O Box 649 – 10100, Nyeri	NCU Building, Gakere Road, Nyeri Town	Nyeri
138	Taqwa Sacco Society Ltd	P.O Box 10180 – 00100, Nairobi	Jamia Plaza, Kigali Street, Nairobi	Nairobi
139	Taraji Sacco Society Ltd	P.O. Box 605 – 40600, Siaya	Mwalimu Plaza, Oginga Odinga Street, Siaya	Siaya
140	Telepost Sacco Society Ltd	P.O Box 49557 – 00100, Nairobi	City Square Post Office, Haile Selassie Avenue, Nairobi	Nairobi
141	Tembo Sacco Society Ltd	P.O Box 91 – 00618, Ruaraka	Tembo Sacco Complex, Garden Estate Road, Mukima Drive, Nairobi	Nairobi
142	Tenhos Sacco Society Ltd	P.O Box 391 – 20400, Bomet	Tenhos Building, Tenwek, Bomet	Bomet
143	Thamani Sacco Society Ltd	P.O. Box 467 – 60400 Chuka	Thamani House, Chuka Town	Tharaka Nithi
144	The Apple Sacco Society Ltd	P.O. Box 153 – 50305, Kaimosi	Tasccos House, Kapsabet – Chavakali Road, Kapsabet	Nandi
145	The Kenya Bankers Sacco Society Ltd.	P.O. Box 73236 – 00200, Nairobi	The Kenya Bankers Sacco Centre, 3rd Ngong Ave., Nairobi	Nairobi
146	The Noble Sacco Society Ltd	P.O Box 3466 – 30100, Eldoret	The Noble Sacco Building, Ronald Ngala Road, Eldoret Town	Uasin Gishu
147	Times U Sacco Society Ltd	P.O Box 310 – 60202, Nkubu	Nkubu, KCB Road, Nkubu	Meru
148	Topkrim DT Sacco Society Ltd	P.O Box 127 – 40222, Oyugis	Kisumu – Kisii Road, Oyugis Town, Homabay	Homabay
149	Tower Sacco Society Ltd	P.O Box 259 – 20303, Ol'Kalou	Tower Sacco Fosa Building, Ol'kalou Township	Nyandarua
150	Trans – Counties Sacco Society Ltd	P.O Box 2965 – 30200, Kitale	Kapsara, Trans – Counties Sacco Office, Kapsara	Trans Nzoia
151	Trans – National Times Sacco Society Ltd	P.O.Box 2274 – 30200, Kitale	Kitale Teachers Plaza, KANU Street, Kitale	Trans Nzoia
152	Trans Elite County Sacco Society Ltd	P.O Box 547 – 30300, Kapsabet	Former Barclays Bank Building, Kapsabet – Chavakali Road, Kapsabet Town	Nandi
153	Trans Nation Sacco Society Ltd	P.O Box 15 – 60400, Chuka	Mwalimu Centre, DC Road, Chuka Town	Tharaka – Nithi
154	Ufanisi DT Sacco Society Ltd	P.O. Box 2973 – 00200, Nairobi	Development House, Moi Avenue, Nairobi	Nairobi
155	Ukristo Na Ufanisi DT Sacco Society Ltd	P.O Box 872 – 00605 Nairobi	ACK Emmanuel Church Riruta, Nairobi	Nairobi
156	Unaitas Sacco Society Ltd	P.O Box 38721 – 00100, Nairobi	Cardinal Otunga Plaza, Nairobi	Nairobi

157	Uni – County Sacco Society Ltd	P.O. Box 10132 – 20100, Nakuru	Nakuru Municipality Block, 9/37, Generation House, Kijabe Row, Nakuru	Nakuru
158	Unison Sacco Society Ltd	P. O. Box 414 – 10400, Nanyuki	Unison Plaza, Nyeri – Nanyuki Road, Nanyuki Municipality	Nanyuki
159	United Nations DT Sacco Society Ltd	P.O Box 2210 – 00621, Nairobi	United Nations Complex, United Nations Avenue, Nairobi	Nairobi
160	United Winners Sacco Society	P.O Box 1390 - 00515, Westlands	Imani Towers, Umoja Estate, Nairobi	Nairobi
161	Universal Traders Sacco Society Ltd	P.O Box 2119 – 90100, Machakos	Traders House, Syokimau Road, Machakos	Machakos
162	Univision Sacco Society Ltd	P.O. Box 254 – 90200, Kitui	Teachers Plaza, Kitui Town	Kitui
163	Ushuru Sacco Society Ltd	P.O Box 52072 – 00200, Nairobi	Ushuru Sacco Centre, Wood Avenue, Kilimani	Nairobi
164	Vihiga County Farmers Sacco Society Ltd	P.O Box 309 – 50317, Chavakali	Mudete Town, Vihiga County	Vihiga
165	Viktas Sacco Society Ltd	P.O. Box 2183, Nyahururu	Glanin Centre, Nyahururu – Nyeri Road, Mairo Inya, Nyandarua	Laikipia
166	Vision Afrika Sacco Society Ltd	P.O Box 18263 – 20100, Nakuru	Rajdeep House – Kenyatta Avenue, Nakuru	Nakuru
167	Vision Point Sacco Society Ltd	P.O. Box 42 – 40502, Nyansiongo	Borabu Farmers Union Building, Keroka – Sotik Highway, Borabu	Kisii
168	Wakenya Pamoja Sacco Society Ltd.	P.O. Box 829 – 40200, Kisii	Kahawa House, Kisii – Keroka Road, Kisii	Kisii
169	Wakulima Commercial Sacco Society Ltd	P.O. Box 232 – 10103, Mukurukweini	MWD Limited Complex, Mukurweini – Nyeri Road, Mukurweini Town	Nyeri
170	Wanaanga Sacco Society Ltd	P.O Box 34680 – 00100, Nairobi	Kenya Meteorological Department, Ngong Road, Dagoretti	Nairobi
171	Wananchi Sacco Society Ltd	P.O Box 910 – 10106, Othaya	Wananchi Building, Othaya	Nyeri
172	Wanandege Sacco Society Ltd	P.O Box 19074 – 00501, Nairobi	Wanandege Plaza, Old North Airport Road, Nairobi	Nairobi
173	Washa Sacco Society Ltd	P.O. Box 83256 – 80100, Mombasa	Ralli House, Nyerere Avenue, Mombasa	Mombasa
174	Waumini Sacco Society Ltd	P.O Box 66121 – 00800, Nairobi	Applewood Adams 2nd Floor, Ngong Road, Nairobi	Nairobi
175	Wevarsity Sacco Society Ltd.	P.O. Box 873 – 50100, Kakamega	Wevarsity Plaza,Kakamega–Webuye Road,Kakameg	Kakamega
176	Winas Sacco Society Ltd	P.O. Box 696 – 60100, Embu	Winas House, Embu Township	Embu
177	Yetu Sacco Society Ltd	P.O Box 511 – 60202, Nkubu	Yetu Sacco Building, Nkubu Town, Meru	Meru

Source: SASRA (2025)