FACTORS INFLUENCING THE USE OF MODERN TECHNOLOGY BY MICROFINANCE BANKS AND CREDIT-ONLY MICROFINANCE INSTITUTIONS

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DECLARATION

I declare that this thesis has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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ABSTRACT

Financial inclusion aims to ensure that everyone, including the poor, has access to financial services, thereby promoting economic growth and development. Financial institutions have adopted new technologies to accelerate financial inclusion. These technologies include cloud computing, blockchain, artificial intelligence, machine learning, deep learning and robotic process automation. However, given that technology adoption depends on various aspects from the rate of technological changes, institutional features, products and even the nature of clients for microfinance banks and institutions, there is little empirical evidence on the rate of adoption and relevance of new technologies by microfinance banks and credit only institutions. The three main objectives of the study were first, to assess the level of adoption of new technologies in financial inclusion, identify organizational features that influence the type of new technologies adopted and obtain the perspectives of the microfinance banks and credit-only institutions on these new technologies. This study was anchored on Diffusion of Innovation and Financial Intermediation theories, The main population was 13 Microfinance banks licensed by the Central Bank of Kenya as at December 2022 and the 34 Credit only microfinance institutions as listed by the Association of Microfinance Institutions in Kenya in 2022. Primary data was obtained using an online questionnaire and secondary data was obtained from available annual reports for 2022. Both descriptive and multivariate analysis were carried out aided by multinomial logistic regression to establish the organizational factors that may influence the adoption of new technologies. Response was obtained from 39 organizations. Key findings were that all organizations have adopted artificial intelligence, which is ranked as the best technology to promote financial inclusion. However, even though other technologies have been adopted, robotic process automation was the least adopted. Board size reported a significant and positive association with machine learning technology, while profitability, poor asset quality and capital adequacy reported a significant and positive association with deep learning technology. Microfinance banks have adopted cloud computing at a lower rate as compared with credit only microfinance institutions, while MFBs adopt deep learning at a higher rate than that of Credit Only Microfinance institution. Finally, more older organizations have adopted cloud computing as compared to the younger ones. Respondents explained that the main motivation for adopting new technologies was to expand the customer base and reduce operational costs. However, the major challenge of adopting new technologies was costs, due to resource constraints by Microfinance banks and Credit only financial institutions. The key concern for respondents was the fact that customers prioritize using new technology to borrow, with little use of the other services in financial inclusion. These findings are important as they provide empirical evidence on the best technology that aids financial inclusion and areas where key stakeholders can focus to enhance the use of new technologies to promote financial inclusion. Further studies are necessary to include all stakeholders in financial inclusion, with main stakeholder being the customer, to determine the customer experience.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AMFI-K	Association of Microfinance Institutions - Kenya
BC	Blockchain Technology
CBK	Central Bank of Kenya
CC	Cloud Computing
COMFI	Credit Only Microfinance Institutions
DL	Deep Learning
DOI	Diffusion of Innovation
FI	Financial Intermediation
FinTech	Financial technology
MFB	Microfinance Banks
MFI	Microfinance Institutions
ML	Machine Learning
RPA	Robotic Process Automation

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

The importance of technology in business and other aspects of human life cannot be emphasized more. Atalaya et al. (2013) posit that beside people, technology is a very important resource applied by organizations and businesses for to be competitive in the current dynamic environment. Improved technology reduces operation cost, increases efficiency, and generally increases productivity within the sector (Beatty & Quinn, 2010). Technology has enabled globalization of the world, immensely transforming how companies operate; spurring innovation and progress in many sectors with significant economic development (McKinsey & Company, 2016). A study by Frame et al. (2018) on new innovation-informed by technology has changed and led to many business products, services, production processes and organizational structures in the business environment.

The financial services sector has been a powerhouse of technological innovations (Shkodina, et al., 2018). Aside from Covid 19 that accelerated the urgency to innovate, several factors have contributed to financial services innovations in technology. First to generate new venues of incomes. Second, to improve customer experience given their changing expectations, business disruption occasioned by FinTech. Third, increasing regulation and other compliance requirements. Fourth, automating many processes to make it easier for staff to serve customers efficiently and where necessary for customers to access services on their own. These factors are among many others, nevertheless the financial services sector will continue to innovate at the same pace with technological innovations.

The Digital Banking Benchmark report of 2017 explains that banks and other financial institutions rely on technology to be for competitiveness supported through Fintechs. With computer and internet proliferation, this has led to expansion of digital-based bank products and services. These digital advancements are reshaping the financial ecosystem and the future of banks (McKinsey & Company, 2016). However, the digital banking report of 2017 pointed out that non-traditional competitors such as microfinance banks and other microfinance institutions face challenges to adopt new technologies. The report underscored the necessity for these institutions to enhance their agility in providing services and introducing novel products to sustain their relevance within the financial services industry in the future.

This section reviews the role of microfinance banks and other institutions in financial inclusion and provides a summary of the new technologies that the study focused on and closes with a brief discussion of the research gaps.

1.1.1 The Role of Microfinance Banks and Institutions in Financial Inclusion

The World Bank defines Micro Finance Institutions (MFIs) as institutions that provide banking and other services to low-income individuals, microbusinesses, small-scale farmers, and others that have little or minimal access to standard financial services (CBS, 1999). The Microfinance Act, 2006, meanwhile defines MFI as a financial institution that accepts deposits and which it then lends to others or uses to finance its operations; or as a financial institution that offers low-income households and micro and small businesses loans or other facilities; Taking deposits and not taking deposits (MFI Act, 2006).

Financial inclusion is where business entrepreneurs and individuals access financial products and services with the view to satisfying their needs and those of their clients (Sharma, 2016). It has to do with saving, making, and receiving payments, transacting, receiving credit, and insurance (Atkinson & Messy, 2013). All organizations—especially small enterprises in least developed countries—need to be financially inclusive. Financial inclusion makes it easier for small and sized firms to get financing that they could use to finance business investments. It also aids in financial savings, which allows for future investments and risk management. Enhancing access to insurance services and products is made possible by financial inclusion, and this is essential for mitigating company vulnerabilities. (Sarma & Pais, 2012).

The Central Bank Supervision Annual report indicates that the Kenya Banking sector asset base grew by 11 per cent to Ksh 6.0 trillion in 2021 from Ksh 5.4 trillion in 2020 (CBK, 2022). This increase is mainly attributed to the growth in investments in government securities, loans, and advances. As of December 31, 2021, Kenya's banking sector comprised of 38 commercial banks and 14 microfinance banks (MFB).

Malenya and Kariuki (2017) define microfinance institutions (MFIs) as any organizations that engage in activities that include the provision of financial services such as credit, savings, and insurance to low-income individuals. Just like banks, microfinance banks play an important role in financial inclusion. The Central Bank of Kenya supervision report CBK (2021), highlights that the three largest microfinance banks in Kenya have about 80 percent, while about 19 percent of the market share is held by six medium sized microfinance banks. Unfortunately, 5 microfinance banks have less than 1 percent of the market share. The most common activity undertaken by microfinance banks was lending, as with the net loan portfolio accounting for about 55 percent of the total assets for microfinance banks. Meanwhile, customer deposits were estimated at 70 percent and borrowing from other banks mounted to 15 percent. The reported linked the growth in deposits resulted from mobilization of funds through the expansive branch network and various business channels. Microfinance banks, just like commercial banks perform intermediary roles in the economy by delivering basic functions of deposit taking, lending money, bank assurance and channels of transfer services. They however play a significant and unique role in promoting financial inclusion, as they are uniquely positioned to reach the poor and enjoy greater acceptability among the poor due to their flexibility in operations as noted by Malenya et al. (2017).

Unlike their counterparts, there is limited information about credit only microfinance institutions in Kenya (COMFI). According to the Association of Microfinance Institutions in Kenya (AMFI -K) sector report, there are 37 Credit only MFIs by end of December 2021. However, the website only provides information about 34 COMFIs. These usually provide credit to small and medium sized entities and individuals without receiving deposits. However, a few of the clients save with them. They operate like a revolving fund i.e., raising funds from various sources to provide credit. Out of the 34, AMFI collected data on 13 COMFIS. The total number of active loans stood at about 380,000, the average loan size stood at Ksh50,000 with the least and highest average loan size being Ksh10,000 and Ksh1,000,000 respectively. The total loan portfolio was sh.120 billion.

1.1.2 New Technologies in Microfinance Banks and Institutions

This section provides a summary of the new technologies that are relevant within the context of financial services. These include Cloud Computing (CC), Blockchain technology (BC), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) and Robotics Process Automation (RPA).

Cloud computing (CC) is a model for giving banks easy access to a shared pool of reconfigurable computing resources across the network, whenever they need to access it. These consist of things like servers, networks, software, storage, and services that may be quickly made available and provided with minimal administration labor or contact with the service provider (Parry & Bisson, 2020). There are three cloud computing models (Marinescu, 2017). The first option is using the software as a service that helps develop banking institutions. Instead of depending on conventional applications that are kept on their server or computer, the microfinance bank institutions can simply use this software to access internet-hosted software services through their browser. The banking institution can purchase or lease computers and disk space from an internet service provider under the second option, infrastructure as a service. They will be able to access information via a private network or the internet thanks to this. The final choice is platform as a service, which lets the bank rent hardware, operating systems, storage, and network capacity through infrastructure as a service, together with the related software and server environments. According to Yaga et al. (2019) blockchains (BC) are a type of digital ledger that cannot be altered without leaving clear evidence of having been altered. In their most basic form, blockchains allow a group of people to use a shared ledger to track transactions amongst themselves. Once a transaction is recorded on a blockchain, it cannot be altered due to the way the network was built, making it impossible to change the transaction. Stated differently, a Blockchain is an immutable, decentralized ledger that facilitates the recording of transactions and asset management in a business network. Blockchain is also used to create decentralized financial systems that allow for peer-to-peer transactions without the need for intermediaries such as banks. However, within the banking sector blockchain technology is popular for payments and financial transactions. Vassilopoulos (2010) described Artificial Intelligence (AI)as the branch of computer science that deals with developing algorithms and techniques that can simulate or even recreate the human mind's capabilities. Chukwuani and Egiyi (2020), explained that AI aims at making intelligent machines that can respond in human like ways. AI therefore refers to the simulation of human intelligence in machines that are programmed to think and learn like humans resulting in machines that can perform tasks that typically require human intelligence such as decision-making. Thanks to AI tools, financial institutions can analyze higher volume of both structured and unstructured data much faster. In addition, the increased number of variables boosts the quality of the analysis, as knowledge of customers is better, and the results obtained are more precise (Fernandez, 2019). Machine learning (ML) is a type of AI that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Kapoor et al. (2021) explained that ML is used to improve various areas of the finance industry such as payment transactions, fraud detection, forecasting of returns, portfolio construction, and risk modeling. ML is important because it gives organizations a view of trends in customer behavior and business operational patterns, as well as supports the development of new products.

At its simplest, Deep Learning (DL) is a way to automate predictive analytics. While traditional machine learning algorithms are linear, deep learning algorithms are stacked in a hierarchy of increasing complexity and abstraction (Chai & Li, 2019). DL combines machine learning and artificial intelligence (AI) to imitate the way humans gain certain types of knowledge. DL is an important element of data science, which includes statistics and predictive modeling. It is extremely beneficial to data scientists who are tasked with collecting, analyzing, and interpreting large amounts of data; deep learning makes this process faster and easier (Han et. Al., 2018). In addition, DL aids financial services institutions in forecasting macroeconomic conditions, risk, and portfolio management (Almahdi & Yang, 2017).

Robotic Process Automation ("RPA") refers to the automation of tasks that were previously performed by humans, this automation can be applied in business processes to configure software to do the work previously done by humans resulting in replacing some or all the work previously performed by humans (Lacity , 2015), Ansari et al. (2020) described RPA as an emerging technology that is used to automate structured and stable processes that execute repetitive, manual, rule-based, high-volume, and routine tasks.

robotics in finance and banking can efficiently gather data from different sources for reporting, Loan/mortgage processing, accelerate customer onboarding and enhance customer experience (faster application of Know your customer – KYC) and other aspects such as accounts and loans management (Kaya, et al., 2019).

The current study is motivated in various ways. From the above discussions, digital revolution has been instrumental in transforming how people access financial services worldwide. With the rise of mobile technology, peer-to-peer platforms, and other digital tools, people in remote pockets of the world can now receive formal financial services more conveniently, securely, and affordably. The use of technology in financial services has been an area of interest for researchers and other stakeholders. Some studies have focused on the role of technology in financial services (Wonglimpiyarat, 2019; Li, Liu, and Xie, 2019; Kerenyi, Muller and Brave, 2019) as well as various world bank reports. Other studies have focused on the role of technology in microfinance banks and institutions (Rozzani et al., 2013; Mwela, 2014; Sowmya and Reddy, 2018). Some studies have evaluated the use of specific technologies in financial services such as cloud computing (Misra & Doneira, 2018), Blockchain technology ((Tapscott & Tapscott,2016 &2017), Artificial Intelligence (Fernandez, 2019), Machine Learning (Pothumsetty, 2020), Deep Learning (Ozbayoglu et. Al.,2019) and Robotics Process Automation (Barnet, 2015). A few studies have also looked at the role of technology in promoting financial inclusion (Kouladoum et. Al., 2022).

Even though the studies above indicated a consensus that technology is an enabler of access to financial services, the studies are yet to focus on specific aspects of the extent of use of technology in microfinance banks and institutions. According to FSD (2021) report, technology has enabled individuals to access banking and other credit services through mobile devices, for example mobile and internet banking. The study will focus on microfinance banks and credit only institutions. Studies such as those of Chepkwony (2018) and Tut (2023) report that technology adoption by Kenyan banks is high i.e. the use of technology in almost all the processes. However, for microfinance banks, it is important to establish the extent to which these new technologies are adopted and used in financial inclusion, whether the organizational attributes such as size and age affect the rate of technological adoption. Credit Only MFIS may also lag in adoption of new technologies due to resource constraints.

1.2. Problem Statement

As provided in section 1.1 financial inclusion is an important factor in achieving economic growth. Kim, Yu, and Hassan (2018) found that financial inclusion (measured on various dimensions such as access to banking and insurance services, affordable savings and borrowing) has a positive and significant relationship with economic growth being gross domestic product (GDP).

Bhuvana and Vasantha (2016) established that factors such as financial literacy, low cost, technology, trust, income level, distance and relevant products are some of the important factors and drivers of financial inclusion. Meanwhile, Ulwodi and Muriu (2017) explain that the same factors can also hinder or act as barriers to financial inclusion if various stakeholders do not focus on how they can be enhanced. The critical one is technology.

Financial services now rely on technology for a competitive edge and deliver value to customer. Prior studies have shown that whereas banks are at the forefront in the adoption and use of new technologies, we have little empirical evidence regarding MFBs and COMFIS. As Malenya et al. (2017) explain, these institutions are more effective in promoting financial inclusion, as they target clients who cannot afford the services offered by mainstream financial institutions such as banks and insurance companies. Therefore, institutional factors will likely influence the adoption of new technologies.

MFBs and COMFIS stand to benefit from using new technologies in promoting financial inclusion, but also need to overcome various challenges. Benefits range from operational efficiency, access to more customers and hence increased revenue and profitability However, challenges such as poor infrastructure, lack of knowledge, high risks, strict regulation and compliance, and high costs of operating the new technologies will likely affect the level of adoption of the new technologies (Pathan & Niguthe, 2014).

This study, therefore, aimed to determine the extent and use of new technologies by MFBs and COMFIs. This aimed at shedding light into application of new technologies in financial inclusion, the extent of adoption, institutional factors that may influence the adoption and opportunities and challenges of adopting new technologies.

1.3. Research Objectives and Research Questions

The general objective of this study was to evaluate the application of new technologies by Microfinance banks and credit only institutions. The specific objectives are:

1. To assess the extent to which microfinance banks and credit-only institutions use new technologies in financial inclusion.
2. To establish organization factors that influence the use of new technologies in financial inclusion by microfinance banks and credit-only institutions.
3. To evaluate the management of microfinance banks and credit-only institutions perspectives on the adoption of new technologies in financial inclusion.

The study is guided by the following research questions.

1. To what extent do microfinance banks and credit only institutions use new technologies in financial inclusion?
2. Which organization factors that influence the use of new technologies in financial inclusion by microfinance banks and credit only institutions?
3. What are the managements' perspectives on adoption of new technologies in financial inclusion?

1.4. Scope of the Study

This study used the 13 MFBs as licensed by the Central Bank of Kenya as of December 2022 and the 34 COMFIs members of the Association of Microfinance institutions by 2022 as given in appendix III. The study used both secondary data and primary data. The secondary data was largely drawn from the Banking Annual Supervisory reports and microfinance bank's audited financial statements year 2022 (for those that publish). The primary data was administered by way of online questionnaire that targeted the senior management (Mainly Chief Executive Officers, Chief Finance Officers and Chief Information Officers).

1.5. Significance of the Study

1.5.1 Policy Makers and Regulators

The findings in this study aimed to contribute to the current efforts spearheaded by bodies such as the World Bank and the government to promote financial inclusion. The findings from this study provide national policy makers with an understanding of the issues associated with the adoption of new technologies, to inform development of regulations and development of ICT policies. The findings also provide the Central Bank of Kenya policies to enhance compliance and regulation by MFBs while promoting the adoption of technology-based innovations.

1.5.2 Microfinance Banks (MFBs)

The insights from this study will likely improve MFBs decision in allocating investment resources in various technologies that enhance financial inclusion and therefore financial performance. The study provides insights into opportunities for adopting new technologies for achieving financial inclusion, so that they can implement. In addition, the study informs the key challenges in adopting new technologies and strategies to overcome them. The attempts to answer questions whether MFBs should adopt or continue exploring technology-based products in conduct of business and helps MFBs identify the benefits and pitfalls of technological developments and adoption.

1.5.3 Credit Only Microfinance Institutions (COMFIS)

Just like MFBs, COMFIS also stand to benefit from the findings of the study, even though their scope of operation is narrower than that of MFBs. First the level of adoption will inform the COMFIs of the relevance of new technologies in credit only lending. Second, the COMFIs will establish the benefits of adoption of new technologies and challenges to adoption and how they can overcome these challenges.

1.5.4 Researchers and Academicians

Given the scarcity of empirical literature on adoption of new technologies by MFBs and COMFI, the findings from this study aim to contribute and even extend empirical literature. First, the study provides a contribution to the body of knowledge by providing insights into the rate of adoption of new technology by the units of study i.e. MFBs and COMFIs. Secondly, the study fills the knowledge gaps regarding relevance of new technologies by MFBs and COMFIs. Finally, the study provides conclusions and recommendations for future research areas.

CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

Chapter two first highlights the theoretical framework that supports the study. Secondly, the chapter provides a review of empirical studies about the application of new technologies in the financial services, and organization characteristics that influence the adoption of new technologies. The chapter also presents a summary of knowledge gaps arising from this review which informs the conceptual framework and operationalization of the study variables that are presented toward the end of the chapter.

2.2. Theoretical Review

The theoretical principles that relate to the application of new technologies include The Diffusion of Innovation Theory (DOI) and Financial Intermediation Theory (FI).

2.2.1 Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation (DOI) Theory was proposed by E.M. Rogers in 1962, and describes how new ideas and technologies spread through a population. According to Almaiah et al. (2022), the diffusion of innovation theory investigates methods of infusing novel technologies across a social system. Taherdoost (2018) commented that DOI can be used at both organizational and individual levels and offers a theoretical foundation that can be used to discuss adoption at a global level. In expounding on the theory further, Rogers (2003) described adoption as a decision to make full use of an innovation as the best course of action available and further explained that diffusion is a process through which an innovation is communicated through certain channels over time among the members of a social system. The DOI model integrates three major components, namely, the characteristics of the adapter, the characteristics of the innovation, and the innovation-decision process.

The characteristics of the innovation involve five key constructs that have been proposed as effective factors in any innovation acceptance, these variables are relative advantage, which explains the degree to which an innovation is seen as better than the idea it replaces, compatibility, which explains how consistent the innovation is with the values, experiences, and needs of the potential adopters, observability, which explains the extent to which the innovation provides tangible results, trialability, explains the extent to which the innovation can be tested before a commitment to adopt is made and perceived complexity which explains how difficult the innovation is to use (Taherdoost, 2018). In this study, DOI is relevant to the extent organizational differences will influence the rate at which MFIS and COMFISs will adopt new technologies.

Adopters are categorized in five groups (Taherdoost, 2018). These are innovators, who are people that want to be the first to try the innovation and are willing to take risks, early adopters, who are people that represent opinion leaders and are already aware of the need to change and therefore are very comfortable adopting new ideas, laggards, who are people that are bound by tradition and very conservative and therefore very skeptical of change and are the hardest group to bring on board, the late majority who are people that are skeptical of change and will only adopt an innovation after it has been tried by the majority, and finally the early majority who are people that are rarely leaders, however, they adopt new ideas before the average person. The implication is that in adopting new technologies, some MFBs and COMFIS will be categorized at different levels, with some leading while others following.

Five steps for the innovation-decision process have been identified and these include awareness, interest, evaluation, trial, and adoption. In conclusion, DOI focuses on system characteristics, Institutional features, and environmental aspects in assessing the adoption of new technologies. Numerous studies have used diffusion of innovation theory in examining adoption of new technologies such as Al-Jabri and Suhail (2012), Lin and Chen (2012) and Zhu et al. (2017).

Despite its wide use in various studies that evaluate the adoption of technologies, Diffusion of Innovation technology has its limitations as pointed out by Damsgaard (2001) and Rogers (2003). First, differences in technology, the assumptions about the rate of adopting new technologies may not be grouped as per the components provided. Secondly, adopters of new technology may fall in more than one category. Finally, the adoption of new technology will likely be affected by different sectors.

2.2.2 Financial Intermediation Theory (FI)

Financial intermediation theory was developed in the 1960's by Gurley and Shaw (1960). Financial Intermediation theories emphasize the roles of banks in the efficient allocation of funds, reduction of market failures, and asymmetric information which is a key feature to successful financial inclusion (Kalunda & Ogada, 2019). The generation of this reliable information and reduced transaction costs leads to profitable and stable financial institutions. Here, financial intermediaries function as agents of individual lenders and borrowers, banks exploit economies of scale or scope in the transaction technology brought about by new technologies in financial services.

Barney (2004) notes that firms that have embraced new technologies can execute transactions faster, exchange information more rapidly and innovate through new business processes very quickly. For example, InfoDev (2013) noted that transactions in cash required a bank, or regulated payment system operator to carry it out on behalf of a customer. Technology has reduced non-cash transactions supporting financial intermediation, hence the relevance of FI theory.

FI is premised on the fact that intermediaries serve to reduce transaction costs and information asymmetries. Financial institutions use funds from surplus units to lend to deficit units in the economy, intermediation reduces transaction costs and reduces information asymmetry. Financial intermediaries therefore act as middlemen to provide this information but at affordable transaction costs (Douglas, 1984). Development in information technology, financial sector deepening and deregulation has been proven to reduce transaction costs and enhancement of information availability. Financial intermediaries exist due to market imperfections. As such, in a perfect market situation, with no transaction or information costs, financial intermediaries would not exist (Markides, 2014).

Financial intermediaries can make far greater advances than most people could by combining numerous small deposits. This is because most savers are hesitant to lock up their money for the long term, while most borrowers want to borrow money for shorter periods of time. Financial intermediaries can meet the needs of lenders and borrowers by creating a floating pool of deposits. (Swamy & Tulasimala, 2012).

According to Scholtens and Wensveen (2000), even though financial intermediation theory is very useful in explaining the process of linking borrowers and lenders in economics, FI theory might be limited in two ways. First, the assumption is that financial institutions only play the role of intermediation. However, financial institutions also play other roles such as risk management and social development. Secondly, FI theory assumes that financial markets are static, whereas they are dynamic. The dynamic nature means that the role of financial intermediation can be made redundant by new technologies.
FI theory is relevant for the study since MFB and COMFIS are intermediaries. The study therefore explored the extent to which new technology is deployed to enable MFBs and COMFIS to become better intermediaries and promote financial inclusion (Swamy & Tulasimala, 2012; Markides, 2014).

The study, therefore, apply both the DOI and FI theories. The study applied the component of organization characteristics in the DOI theory and adopter characteristics in the FI theory to achieve the first and second objectives of identifying the level of usage of new technologies in the finance function and identifying the features of MFBS and COMFIS and their technologies. Organization characteristics were used as independent variables for the characteristics of the organization according to DOI. These independent variables were expected to provide useful insights into the level of complexity involved in the diffusion and adoption of innovations by MFBs and COMFIS.

2.3. Empirical Theory

A preview of empirical reviews of previous studies on the adaptation of new technologies and their application in financial services is examined in the section below.

2.3.1. Empirical studies on the adoption of new technologies and their application by microfinance institutions

As highlighted in Chapter One, empirical literature on the adoption of new technologies by MFBs are few, and to the best of knowledge non on COMFIs. This section provides a broad highlight of a few studies carried out on the role of technology in financial services being spearheaded by banks, then microfinance institutions and a few that have focused on new technologies.

Technology has been playing an increasingly important role in financial services. Empirical studies have discussed the ways in which technology has transformed the financial industry, and the impact it has had on everything from banking to investing (Wonglimpiyarat, 2019; Li et al., 2019; Kerenyi et al., 2019). One major way in which technology has impacted financial services is through the rise of online banking. Another area in which technology has transformed financial services is through the rise of robo-advisors. These are automated investment platforms that use algorithms to create and manage portfolios for clients. Thirdly, technology has also had a big impact on payment systems where many people now prefer to use digital payment. These systems are not only more convenient, but they're also often more secure than traditional payment methods. Fourthly, technology has played a critical role is in the development of new financial products and services. Fintech companies have emerged as disruptors in the financial industry, using technology to create innovative products such as peer-to-peer lending, crowdfunding (Zavolokina et al., 2016). These products have not only provided customers with new investment opportunities but have also challenged traditional financial institutions to adapt and innovate. Finally, technology has also had a significant impact on financial regulation and compliance. According to Anagnostopoulos (2018), new technologies have enabled financial institutions to detect and prevent fraudulent activities and comply with regulations more efficiently.

Microfinance institutions (MFIs) have played a significant role in addressing the financial needs of the underserved and the unbanked population (Malenya & Kariuki, 2017). However, their reach has been limited due to several challenges, including lack of infrastructure, low literacy rates, and high transaction costs (Rozzani & Rashidah, 2013). The emergence of new technologies has provided hope for MFIs to overcome these challenges and extend their reach to the unbanked population (Mwela, 2014: Sowmya & Reddy, 2018). Technology has transformed the way MFIs operate, from loan disbursal to repayment. The use of mobile money, digital wallets, and biometric authentication has significantly reduced the cost and time involved in loan disbursal and repayment. MFIs can now reach remote areas and serve customers who were previously considered too expensive to serve. Additionally, technology has enabled MFIs to collect and analyze data on borrowers, which has helped them make informed lending decisions and mitigate risks. Moreover, technology has enabled MFIs to offer a range of financial products, including savings, insurance, and remittance services. This has helped them become a one-stop-shop for all financial needs of their customers. Customers can now access these services through their mobile phones, which has made it convenient and affordable for them.

Some studies have also been carried out to check the extent and use of recent technologies in financial services and a few assess their relevance and application in microfinance. Misra and Doneira (2018), established that banks were the early adopters of cloud computing in the financial services sector. This is economically and technologically driven. However, despite strict regulation on data protection, the authors also explained that increase in customer base over time, banks might eventually force banks to move their core banking functionalities to the cloud because of the benefits of scalability and reduced costs. Munya (2017) carried out a study on adoption of cloud computing by microfinance institutions, mainly SACCOs and reported that 92% of the participating SACCOS had a form of cloud computing.

The role of blockchain technology in financial services has generated a lot of empirical interest (See Pal at al., 2020 for a comprehensive review). Blockchain technology has revolutionized the financial industry in a multitude of ways. According to Tapscott and Tapscott (2016 &2017), the main benefit of blockchain technology is its ability to provide a transparent and secure ledger of transactions. This makes it an ideal solution for financial services that need to keep track of transactions and ensure that they are secure and accurate. With blockchain technology, each transaction is recorded in a block that cannot be altered or deleted, providing an immutable record of all transactions (Chen & Bellavitis, 2020). Another benefit of blockchain technology is its ability to reduce costs and increase efficiency. By eliminating the need for intermediaries and reducing the time it takes to settle transactions, blockchain technology can save financial services companies significant amounts of money (Cocco et al., 2017). Wanke et al. (2022) studied the relevance of blockchain technology for Islamic microfinance. The authors reported that blockchain technology is becoming popular across the Islamic microfinance institutions due to decentralized, immutable, shared, and secure data structure characteristics.

According to Fernandez (2019), artificial intelligence (AI) is transforming the landscape of financial services by revolutionizing the way transactions are processed, analyzed, and executed. AI-powered technologies have the potential to improve the efficiency and accuracy of financial services, while also reducing costs and improving customer experiences. Bhuvana and Vasantha (2021) add that of the primary applications of AI in financial services is in fraud detection and prevention by using machine learning algorithms, to quickly identify and flag suspicious transactions, minimizing the risk of fraudulent activities. AI is also being used to improve investment decisions by analyzing vast amounts of data, AI-powered algorithms identify patterns and trends that human analysts may miss (Institute of international finance, 2016). Another area where AI is making a significant impact is in risk management. By analyzing large amounts of data, AI can identify potential risks and provide early warning signals, allowing institutions to take corrective actions before a crisis occurs. This can reduce the likelihood of financial losses, protect investors, and ensure the stability of the financial system (Danilesson et al.,2017). Machine learning (Pothumsetty, 2020), and Deep Learning (Ozbayoglu et al., 2019) also provide similar benefits to financial services. According to Ashta and Hermann (2021), the use of AI in microfinance banking is revolutionizing the industry by making financial services accessible to more people. AI-powered systems can analyze data and predict trends to help microfinance banks make informed decisions. This technology can help microfinance banks identify potential borrowers, evaluate risk, and predict default rates. Odoh (2018) carried out a study on the use of artificial intelligence in record keeping by Nigerian microfinance banks and established that those banks that apply artificial intelligence had better records.

According to Barnet (2015), Robotics Process Automation (RPA) is rapidly changing the landscape of financial services, with numerous benefits. Financial institutions can automate processes such as data entry, account reconciliation, and fraud detection, which can help reduce errors and improve accuracy. Additionally, RPA can help financial institutions comply with regulatory requirements by ensuring that all necessary documentation is completed and filed on time. This not only reduces the risk of non-compliance but also helps institutions avoid costly fines. Met at al. (2020), adds that RPA can help financial institutions improve customer experiences by providing faster and more accurate responses to inquiries. Customer service representatives can access information more quickly and provide timely responses to customers' questions.

2.3.2. Empirical studies on the influence of organization characteristics on the adoption of new technologies

Several studies have been carried out both for financial and nonfinancial services on the organizational factors that may influence the adoption of new technologies. Salah et al. (2021), explained that organizational characteristics refer to parameters that influence the adoption decision of an innovation. Ilin et al. (2017), described organizational characteristics as different features of an organization such as scope, size, and managerial structure, which may accelerate the adoption of new technology. Several studies have examined the impact of organizational factors such as company size, company profitability, company liquidity, and ownership concentration on the implementation of new technologies providing conclusions about the influence of specific factors on the implementation of new technologies in companies. This section provides an analysis of the various organizational factors that have been previously studied. Ilin et al. (2017) performed a study aimed at identifying the factors that affect the adoption of new technologies in five developing countries in Western Balkan where data from 276 companies were collected and firm size as measured by the log-transformed number of employees used as an independent variable. The study concluded that the firm size factor was found to be non-statistically significant in the adoption of new technologies. Ali et al. (2021) researched critical factors that may have an impact on the acceptance of cloud-based services in local governments in Australia where data was collected from 480 IT staff working in 47 local government organizations. The study utilized the FI theory where independent variables of the organizational context were measured by firm size based on the number of employees and the revenue. The study concluded that organization’s size was significantly and positively related to the adoption and use of cloud technology. Bosman et al. (2020) investigated the role of firm size, access to funds, and industry type in deciding to invest and deploy new technologies by surveying 138 manufacturing firms in Indiana, USA. The study concluded that small manufacturers as measured by the number of employees and lower access to funds as measured by revenue prioritize technology that directly impacts productivity, quality, and safety of manufacturing processes whilst larger manufacturers prioritize enterprise support operations technologies. Firm size was measured using the natural logarithm of the total assets, Liquidity was measured using the ratio of cash assets divided by total assets whilst ownership concentration was measured by the percentage of the capital held by the principal shareholder, and firm performance is measured using ROE (return on equity) ratio. Yulyan et al. (2017) performed a study aimed at determining the effect of good corporate governance and the company's age on the implementation of new technologies in Indonesia. The independent variables representing good corporate governance were the board of commissioners, the board of independent commissioners, the audit committee, and meeting attendance whilst company age was measured as the duration in which the Company had been listed.

Due to the nature of the study, there is little empirical literature on factors influencing the adoption of new technologies by MFBs and COMFIs. Given that these organizations carry out some form of banking services, the empirical literature focuses on factors that may influence banks to adopt new technologies. These include mobile and internet banking.

Banks, as part of financial services, will likely adopt new technologies to enhance cost efficiency and changes in capital can potentially affect the risk appetite of banks and their quality of loan underwriting with direct implications on non-performing loans (Ghosh, 2015). The adoption of new technologies is therefore affected by the banks costs has a direct effect on risk monitoring and thus profitability of banks. For instance, innovations particularly in the payment systems have been associated with improved banking sector performance (Scott, Van Reenen & Zachariadis, 2017). Tiriongo and Wamalwa (2020) examine the effects of mobile money on banking sector stability in Kenya. The study had diverse measures such as capital adequacy, asset quality, profitability, and liquidity conditions as a function of the value of transactions via mobile money services. While the study showed reported growth in value of mobile money transactions, there was a reduction in capital adequacy and liquidity ratios of and an increase in non-performing loan ratio to total loans.

A study by Muthiora (2015) on enabling mobile money policies in Kenya reveals that whereas mobile financial services drive high volumes of transaction for large segment of population, banks may portend operational and liquidity risks. Even though the mobile money financial services is still developing and offers many opportunities, it is becoming more and more important to make sure that regulators are aware of this development and that the regulatory frameworks continues to be compatible and aligned with business models in order to safeguard the stability and financial health of the financial sector. Mobile money as a transaction instrument and payment medium may have an impact on banking sector operations as mobile banking products and services gain traction. The loan books and liquidity circumstances may be impacted by the use of mobile money and other digital financial services, which could have an impact on the financial performance of banks.Rotich et al. (2019) views bank size as a key predictor of financial performance when economies of scale are considered; for instance, when commercial banks attempts to increase its size through mergers and acquisition to gain competitive edge. Olowokure et al; 2015 advocate that uniqueness of banks in terms of assets, deposits, loans, and capital influence the quality of decisions on the activities undertaken by a bank, which in effect, affects the strength of financial performance.

There are studies that associate large banks undertaking new technology and new products to the increase returns such as bank undertaking of bank assurance business (Kristen & Sengupta, 2016). Contrary, other researchers view large banks to be points of regulatory attractions; that are exposed to systemic risks associated with complexities, size, and economic sectors interconnectedness (Tirole et al., 2012). Muhindi and Ngaba (2018) assessed the influence of bank size on the financial performance of banks in Kenya using, capital base, number of branches, number of customer deposits, loans, and advances as key variables. The research study found a positive relationship between size and financial performance measured using ROA.

2.4. Summary of Empirical studies and Research Gaps

The empirical results summarized in section 2.3 have highlighted the focus having been on the role of technology in financial services. Wonglimpiyarat, 2019; Li et al., 2019; Kerenyi et al., 2019 have discussed the growth of online financial services, robo advisers and transformation of payment systems. Technology has transformed the way MFIs operate, from loan disbursal to repayment. The use of mobile money, digital wallets, and biometric authentication has significantly reduced the cost and time involved in loan disbursal and repayment. MFIs can now reach remote areas and serve customers who were previously considered too expensive to serve (Mwela, 2014: Sowmya & Reddy, 2018). There is scarcity on the extent to which MFBs and MFIs in Kenya have benefited from the new technologies.

Studies carried out on new technologies and application in Microfinance have also been carried out. Munya (2017) carried out a study on adoption of cloud computing by microfinance institutions, mainly SACCOs and reported that 92% of the participating SACCOS had a form of cloud computing. Wanke et al. (2022) studied the relevance of blockchain technology for Islamic microfinance. According to Ashta and Hermann (2021), the use of AI in microfinance banking is revolutionizing the industry by making financial services accessible to more people. AI-powered systems can analyze data and predict trends to help microfinance banks make informed decisions. This technology can help microfinance banks identify potential borrowers, evaluate risk, and predict default rates. Longinus (2018) carried out a study on the use of artificial intelligence in record keeping by Nigerian microfinance banks and established that those banks that apply artificial intelligence had better records. However, the role of Robotics Process Automation in Microfinance has not been documented. This study therefore aimed to extent these studies and focus on the relevance of the new technologies in MFBs and COMFIs in Kenya.

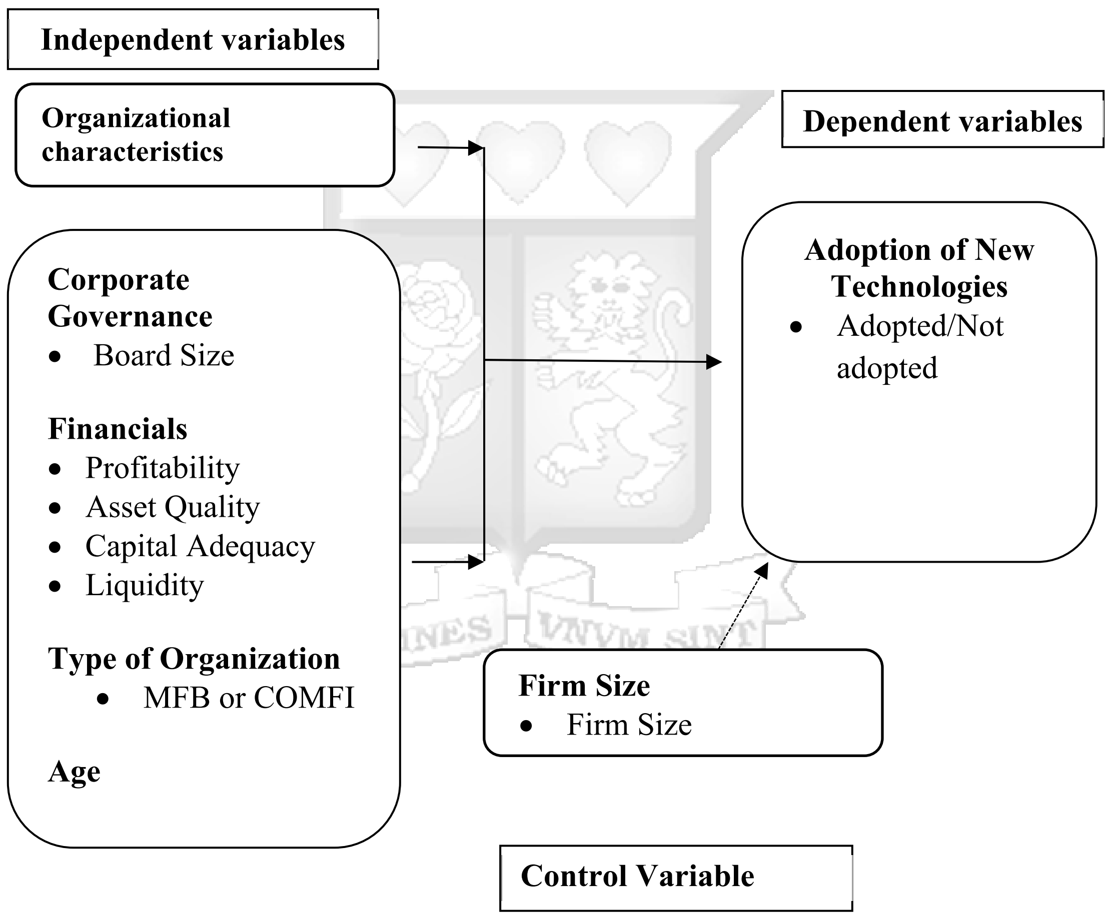
Other studies have been carried out to evaluate the organizational features that influence the adoption of new technologies. There is little if any studies on MFBs and COMFIs, hence this study borrowed on financial and non-financial organizations features as summarized in the conceptual framework.

2.5. Conceptual Framework

The conceptual framework is summarized in the next page. It focuses on objective Two. From the framework, the dependent variable will be measured as a dichotomous variable whereby 1= application of new technology by the MFB and COMFI 0= new technologies have not been applied in the organization. The literature review section identified organizational characteristics that have been used in previous studies and their impact on technology adoption. In this study, company characteristics have been grouped into three dimensions, namely, company financial metrics, other company features, and finance function features.

The figure below shows the independent variables and dependent variables that the study shall focus on. Based on prior studies, organizational size and age have been used as moderating variables.

Figure 2.1 Conceptual Framework



2.6 Operationalisation of the Variables

Table 2.1 indicates the criteria for the operationalization of the independent, control and dependent variables of the study. The measurements, supporting studies, study-based theories and the test of variables are highlighted.

Table 2.1 Operationalization of Variables

Variable	Measurement of Variable	Supporting Past Studies	Supporting Theories	Data Source	Analysis
Dependent Variables					
Adoption of New Technology*	Not adopted = 0 Adopted = 1		DOI and FI	Questionnaire	Descriptive
Independent Variables					
Corporate Governance –	• Board Size	Arthur (2017); Asante, et al. (2014).	DOI and FI	Annual Financial reports and Questionnaire	Panel Data Analysis
Financial Performance	• ROE (Profit after tax/Equity)	Kiemo & Mugo (2021), Dzombo et, al (2018)	DOI and FI	CBK Annual Reports, Banks Audited Financial Statements and Questionnaire	Regression
Asset Quality**	• Non-Performing Loans (NPL)	Kiemo & Mugo (2021), Dzombo et, al (2018) & CBK (2021)	FI	CBK Annual Reports, Bank Annual Supervision Reports, Financial Statements and Questionnaire	Regression
Capital Adequacy	• Capital Adequacy Ratio (Ratio of Capital to risk weighted assets)	Kiemo & Mugo (2021), Dzombo et, al (2018) & CBK (2021)	FI	Bank Supervision Annual Reports, Banks Financial Statements and Questionnaire	Regression

Liquidity	• Total Liquid Assets to Total Short-term Liabilities	Kiemo & Mugo (2021) and CBK (2021)	FI	Bank Supervision Annual Reports, CBK Reports and Questionnaire	Regression
Type of Organization	• MFB =1 COMFI = 0	N/A	DOI	Annual Report and Questionnaire	Regression
Age	• No of years operating				
Control variable					
Size***	• Log of Total Assets	Misati et al (2021) & Kiemo & Mugo (2021)	FI	Bank Supervision Annual Reports and Questionnaire	Regression

*In the questionnaire, the participants were asked to indicate if not adopted, whether they are considering adopting. But the Likert as not used in the analysis, rather the binary aspect.

**Some empirical studies use the ratio of non-performing loans to total loans as a measure of asset quality, while others use the level of nonperforming loans. The higher the ratio and the amounts the poor is the asset quality. The study adopted level of nonperforming loans, due to challenges standardizing the metric. Regulators usually give minimum guidelines for setting levels of non-performing loans for microfinance banks.

***Even though the total asset has been used as a measure of size, alternative approaches may include revenue (interest income), number of employees, and number of branches (Muhindi & Ngaba, 2018). This information was also obtained from the data.

DOI- Diffusion of Innovation

FI – Financial Innovation

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

Chapter three provides the methodology for the study. It specifically highlights the research philosophy, research design, target population and sampling, data collection and analysis, validity and reliability, and concludes with ethical considerations.

3.2 Research Philosophy

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

Positivism is concerned with uncovering the truth and presenting it by empirical means (Henning et al., 2004). The positivistic philosophical foundation is based on real facts, objectivity, neutrality, measurement, and validity of results (Saunders et al., 2007). Its foundation is that observation and reason are effective in understanding human behaviour and that true knowledge is based on experience of senses and can be obtained by observation and experiment. Positivists believe in realism, whereby reality is assumed to exist, and reality is objectively given and is measurable using properties which are independent of the researcher and his or her instruments; in other words, knowledge is objective and quantifiable.

Postpositivism philosophy believes that people have subjective experiences of the external world. They believe that reality is socially constructed. According to Myers (2009) the premise of postposivist researchers is that access to reality is only through social constructions such as languages, consciousness, and shared meanings. Subjective paradigm is underpinned by observation and interpretation, thus, to observe is to collect information about events, while to interpret is to make meaning of that information by drawing inferences, which tend to be subjective.

This study was anchor mainly on positivism philosophical approach (for the first two objectives) and minimally, on post positivism, for the third objective which aimed to obtain the subjective views of MFBS and COMFIS in the relevance of new technologies.

Similar studies by other scholars, Muriithi (2016) and Kithinji (2018) used positivism philosophical approach.

3.3 Research Design

Research design recommends the collection and analysis of data with the aim of conducting the research efficiently (Tashakkori, & Teddlie, 1998). Research design provides issues such as techniques to be used for data gathering, sampling and tools for data collection. The current study used mixed method research design, having both quantitative and qualitative designs. The mixed method approach was implemented in one phase i.e. concurrent triangulation, where both quantitative and qualitative data was collected at the same time and interpreted together (Creswell, 2009).

Creswell and Tashakkori (2007) explain that the application of rigorous quantitative research to evaluate the number and frequency of constructs, as well as rigorous qualitative research to examine their meaning and comprehension, is deliberate. The goal is to combine the advantages of both quantitative and qualitative data collection methods to create a comprehensive interpretive framework that can lead to new insights into the issue or potential solutions. The first two objectives are quantitative in nature with the third objective being qualitative.

3.4 Population and Sampling

A population refers to an entire group of individuals, events or objects having a common observable characteristic about which a researcher is interested in (Sekaran & Bougie, 2016). It comprises of all potential participants that can make up the study group (Kumar, 2008). The study targeted all the 13 MFBs listed by Central Bank of Kenya and 34 COMFIs listed by AMFI-K by end of 2022. This information is provided in their respective websites. Given the small numbers for each group, the study did not use sampling but rather targeted all the organizations thereon. The study targeted Chief Information Officers, or any person equivalent or senior.

3.5 **Data Collection and Tools**

The study collected data from secondary sources and primary sources. Secondary data was collected from secondary sources of CBK Bank Supervisory reports and specific MFB annual reports for the year 2022. Primary data was collected using an online questionnaire capturing information relating to the variables under study. The questionnaire was structured, and the questions were a mixture of yes/no, different levels of the Likert Scale, structured and unstructured, with open ended questions. See Appendix II for the questionnaire used.

3.6 Data Analysis

Beside descriptive statistics analyzing levels of adoption and other organizational features, multivariate data analysis was used in this study to establish the influence of organizational features on the adoption of new technologies by the MFBs and COMFI. The variables were grouped into corporate governance variables (board size), Financials (Profitability, asset quality, capital adequacy and liquidity), type of organization (MFB or COMFI) and moderating variables being size (Total Assets) and age (Years in operation). Given that the adoption of new technology takes a binary status, while the independent variables are categorical or continuous, a multinomial logistic regression model was used (Gujarati, 2011). The regression model is provided as follows:

$$\text{Log}\,(P/1\text{-}P) = \alpha_i + ß_1 BS + ß_2 ROE + ß_3 AQ + ß_4 CA + ß_5 LQ + ß_6 MFB + ß_7 AGE + ß_8 TA + é$$

While β represents the coefficient for the variables, the meaning of the rest of the variables is provided in Table 3.1.

Table 3.1 Summary of variables in the regression model

Symbol	Main Variable	Measurement Variable
P	P is the probability of the dependent variable taking on the value 1 (as opposed to 0) where 1 = New technologies have been adapted and 0 = New technologies have not been adapted	
BS	Corporate Governance –	• Board Size
ROE	Financial Performance	• ROE (Profit after tax/Equity)

AQ	Asset Quality*	• Non-Performing Loans (NPL)
CA	Capital Adequacy	• Capital Adequacy Ratio (Ratio of Capital to risk weighted assets)
LQ	Liquidity	• Total Liquid Assets to Total Short-term Liabilities
MFB	Type of Organization	• MFB =1 COMFI = 0
AGE	Age	• No of years operating
TA	Size**	• Log of Total Assets
é	Error term	•

Further diagnostics on the model are discussed in chapter four, together with the results and findings.

The qualitative aspects of the questionnaire such as benefits and challenges of adopting new technologies, justification of using certain technologies and the role of new technologies in achieving financial inclusion were analyzed using descriptive statistics and a summary of the key points highlighted by the management of the MFBs and COMFIs.

3.7 Research Quality

Research quality aimed at enhancing the credibility of the study. Quality considers both the validity and reliability of the collected data. Validity is the extent to which the research measures what it aims to measure (Creswell, 2014). On the other hand, reliability ensures the consistency of the results over time and with different researchers (Mohajan, 2017). In this study, a combination of qualitative and quantitative research methods was employed to increase the validity and reliability of the findings. Structured questions in the questionnaire provided more standardized and generalizable data. Additionally, the triangulation of multiple sources of data by using mixed methods enhanced the validity and reliability of the study.

3.8 Ethical Considerations

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

CHAPTER FOUR: RESULTS AND FINDINGS

4.1 Introduction

Chapter Four presents the results and findings of the study. The section begins with respondents' details, followed by organization details, then the use of new technologies in financial inclusion. Under the use of new technologies, the section provides more descriptive statistics, bivariate statistics and multivariate statistics.

4.2 Results and Findings

4.2.1 Respondents Details

Out of the 45 respondents targeted, 39 were able to provide feedback (about 87% response rate). The initial response rate was low, and therefore effort was required through emails, follow-up phone calls and organizational visits. The six organizations that had not responded had promised to fill in the questionnaire, but had not done so, by the time of analysis. However, to avoid further delays in completing the study, the analysis proceeded without the remaining six respondents. As explained in the chapter three, the target respondents were mainly the Chief Executive Officers (CEO), Chief Information Officers

Figure 4.1 Summary of the respondents for the study

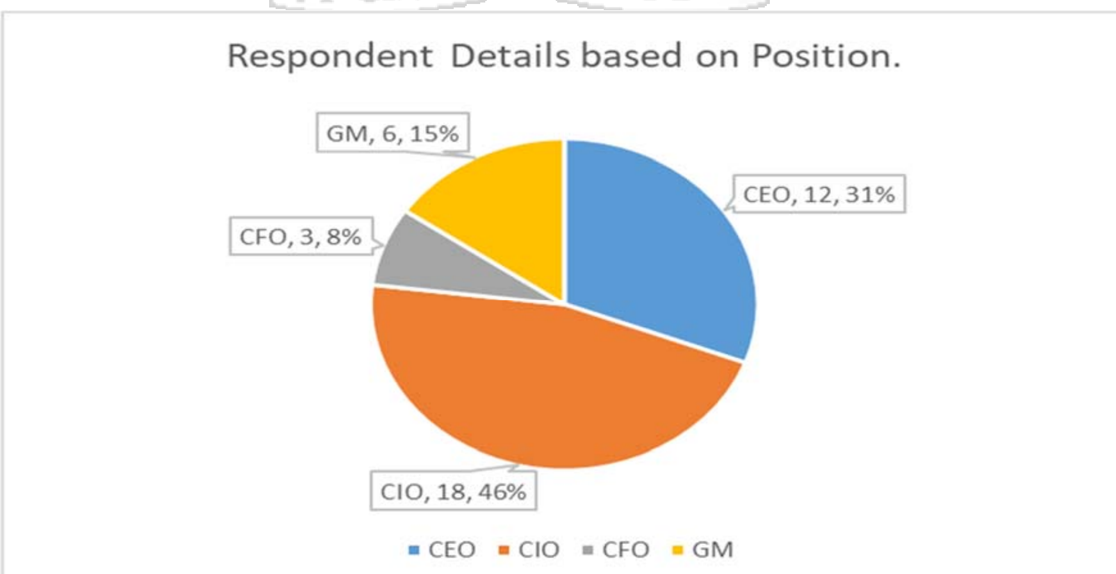


Figure 4.1 explains that majority of the respondents were the Chief Information Officers (CIO), followed by Chief Executive Officer (CEO) and then the General Managers (GM). Only 3 Chief Information officers (CFO) participated in the study.

Question 2 of Part A requested the respondents to indicate the number of years spent in the position.

The summary statistics are provided as follows in Table 4.1.

Table 4.1 Duration in Position

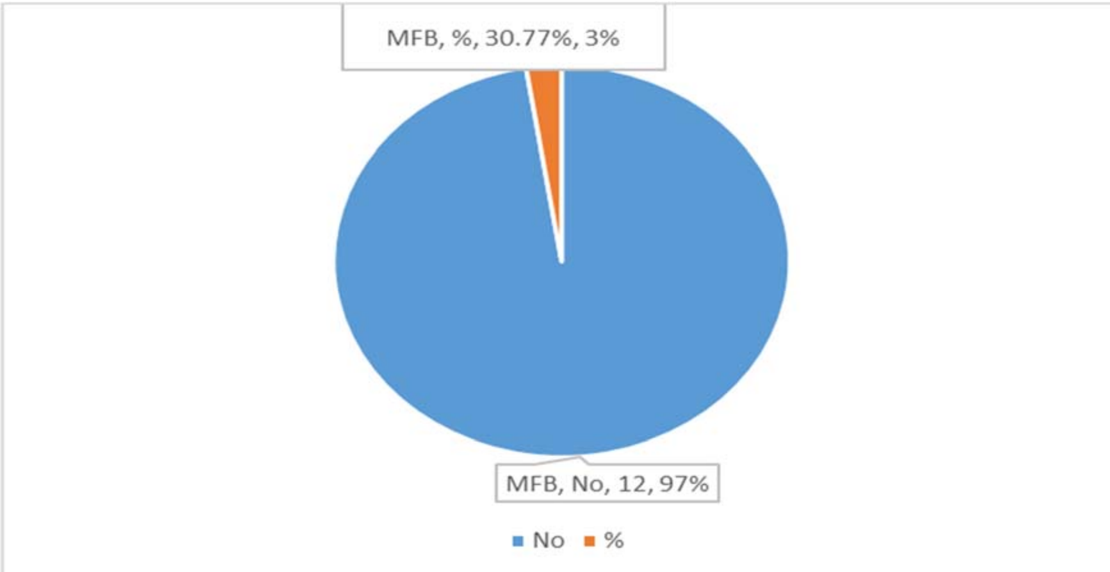
Mean	10.38461538
Standard Error	0.673996865
Median	10
Mode	10
Standard Deviation	4.209109073
Sample Variance	17.71659919
Kurtosis	2.849340014
Skewness	0.950004395
Range	22
Minimum	3
Maximum	25

Table 4.1 highlights that the average number of years a respondent has been in the position in an organization is 10 years, with the minimum being 3 years and maximum being 25 years.

4.2.2 Organizations' Details

On Question one, the study had 12 MFBI and 27 COMFI as summarized in Figure 4.2.

Figure 4.2 Categories of Respondents



The bulk of the respondents were from Credit Only Micro finance institutions.

On question two and three regarding the age of the organization, and the number of board members, Table 4.2 provides a summary of the descriptive statistics:

Table 4.2 Summary Descriptive Statistics - Age of organization and size of board

	Age	Board Size
Mean	18.82051282	8.153846154
Standard Error	0.848807845	0.276224941
Median	19	8
Mode	20	7
Standard Deviation	5.30080329	1.725024203
Sample Variance	28.09851552	2.975708502
Kurtosis	-0.141480796	-0.659566272
Skewness	-0.146720177	0.009016876
Range	22	6
Minimum	8	5

Maximum	30	11

Table 4.2 highlights that the average duration of operation of MFB and COMFI organizations was 18 years, with the youngest organization having operated for 8 years and the oldest being in existence for 30 years. Likewise, the largest board comprise of 11 board members, with the smallest board having 5 board members, and an average of 8 board members.

On Question Four, types of services provided, Table 4.3 provides a summary of the services provided by number of organizations.

Table 4.3 Services Provided

	Receiving Deposits	Lending	Payment Services	Money Transfers	Insurance
No of Organizations	14	39	21	14	10
% of Organizations	35.90%	100.00%	53.85%	35.90%	25.64%

As expected, all the organizations provide lending, while mostly MFBs receive deposits and most of the others provide payment services, money transfers and a few offer insurance services. However, some of the COMFIs offer services like insurance through their parents rather than directly, while a few MFBs provide foreign currency exchange services for their clients.

On Question five regarding the size of the organization as measured by various approaches, Table 4.4 provides a summary of the descriptive statistics:

Table 4.4 Summary measures of Size of the organization

	Employees	*Interest (Sh.000)*	*Assets (Sh.000)*	*Branches*
Mean	75.1282051	411,000.00	2,595,538.46	4.53846154
Standard Error	10.6257764	130,820.76	605,121.84	0.5955822
Median	50	120,000.00	1,090,000.00	3

Mode	60	35,000.00	750,000.00	3
Standard Deviation	66.3579526	816975.3588	3778984.651	3.71940964
Sample Variance	4403.37787	6.67449E+11	1.42807E+13	13.8340081
Kurtosis	2.83423317	11.30348449	8.329190635	6.7832971
Skewness	1.69914609	3.319403216	2.690807622	2.19931369
Range	285	4,010,000.00	18,415,000.00	19
Minimum	15	20,000.00	135,000.00	1
Maximum	300	4,030,000.00	18,550,000.00	20

Table 4.4. shows that the organization with the highest number of employees is 300, but we also have the least number at only 15. In case of revenue, i.e. interest generated from lending, the highest amount earned was approximately sh.4 billion, with the average sector being sh 411 million. The largest organization in terms of size has assets worth sh.18.6 billion, with the smallest organization having assets worth sh.135 million. In terms of branches, the organization with the highest number of branches has 20, while 3 branches is the most common as per the mode.

On Question Six, other performance metrics, Table 4.5 provides a summary of the performance measures.

Table 4.5 Summary measures of Financial Performance metrics

	PAT (Sh.000)	*Loans (Sh.000)*	*NPL (Sh.000)*	*Liabilities (Sh.000)*	*Equity (Sh.000)*
Mean	58,601.96	1,557,323.08	610,813.85	1,946,307.69	649,230.77
Standard Error	58,700.07	363,073.10	145,948.07	453,847.23	151,274.61
Median	800.00	654,000.00	224,600.00	817,000.00	273,000.00
Mode	- 5,400.00	450,000.00	180,000.00	562,000.00	188,000.00
Standard Deviation	366581.81	2267390.79	911445.38	2834275.03	944709.66
Sample Variance	1.34382E+11	5.14106E+12	8.3073311	8.03311E+12	8.92476E+11
Kurtosis	37.94187584	8.329190635	8.26490674	8.328387002	8.331600512
Skewness	6.116755216	2.690807622	2.68650869	2.690705063	2.691115007

Range	2,476,500.00	11,049,000.00	4,419,600.00	13,811,000.00	4,604,000.00
Minimum	- 201,500.00	81,000.00	32,400.00	101,000.00	34,000.00
Maximum	2,275,000.00	11,130,000.00	4,452,000.00	13,912,000.00	4,638,000.00

Table 4.5 Continued, summary of measures of financial performance metrics

	Return on Equity (ROE)	*Capital Adequacy Ratio*	*Liquidity Ratio*
Mean	116.78%	6.643589744	0.246153846
Standard Error	116.66%	0.377197473	0.011055103
Median	0.25%	6.6	0.25
Mode	N/A	8	0.3
Standard Deviation	7.28572041	2.355597463	0.069039096
Sample Variance	53.08172189	5.548839406	0.004766397
Kurtosis	38.99810836	0.634037667	-0.644700642
Skewness	6.244776374	0.515640627	-0.328651812
Range	4,563.24%	11	0.26
Minimum	-13.24%	2	0.1
Maximum	4,550.00%	13	0.36

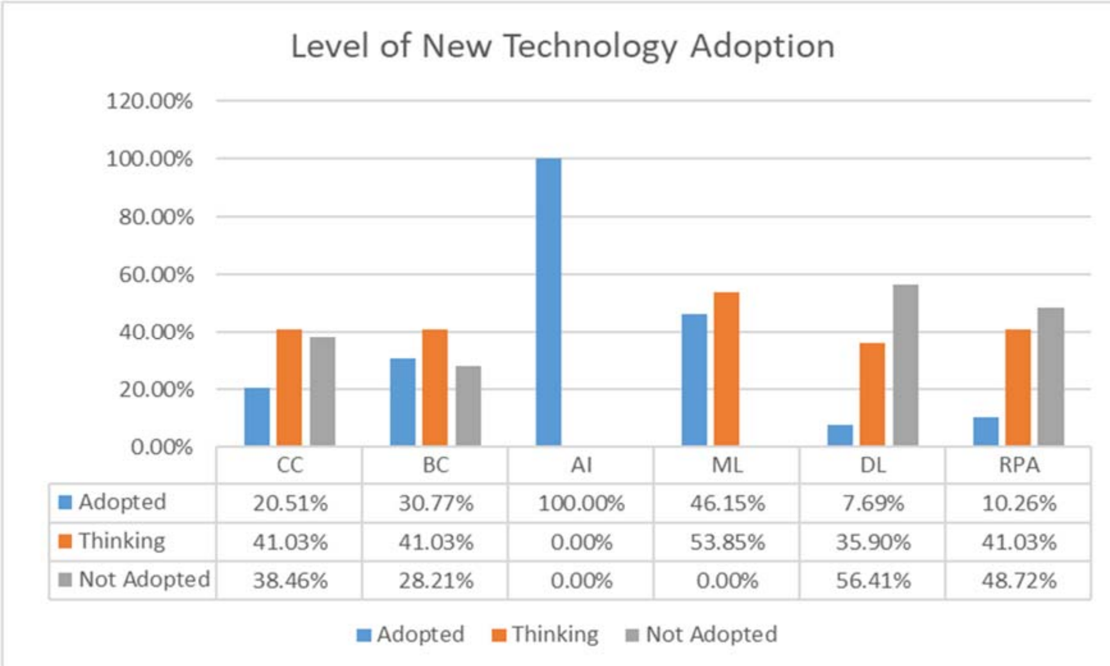
Table 4.5 highlights overall sector performance and position for 2022. The sector has on average, equity worth sh. 650 million, with a return of 116.78%. The average risk as measured in terms of capital adequacy is 6.6 (prescribed industry standard for MFBs is 10). The liquidity risk is high, because average liquidity ratio is 0.25, with a prescribed level of 0.5.

4.2.2 Use of New Technologies in Financial Inclusion

4.2.2.1 Descriptive Analysis – Levels of adoption and other variables

On question One, the respondents provided the following summary of new technology adoption as per Figure 4.3:

Figure 4.3 Level of Technology Adoption



According to Figure 4.3, all organizations have adopted some form of Artificial intelligence. A discussion with a few respondents, highlighted that that most of their banking platforms have been improved to incorporate features of AI, such as Capital One (Capital One is a leading consumer financial services company that uses AI to build customer relationships. Through natural language processing, the chatbot can understand customer queries and provide instant answers.). Machine Language is the next popular technology, then block chain and cloud computing. However, many respondents acknowledged they are considering incorporating aspects of machine Learning and robotic process automation.

On the question 2 regarding the use of technology for the different services, Table 4.6 provides a summary of application of each technology to the different services:

Table 4.6 Application of Technology in different services

	Receiving Deposits	Lending	Payment Services	Money Transfers	Insurance	Others
Cloud Computing	0.00%	0.00%	0.00%	0.00%	0.00%	100.00 %

Blockchain	50.00%	100.00%	100.00 %	75.00%	0.00%	25.00%
Artificial Intelligence	100.00%	100.00%	51.28%	51.28%	20.51%	5.13%
Machine Learning	33.33%	66.67%	66.67%	55.56%	11.11%	22.22%
Deep Learning	0.00%	66.67%	0.00%	0.00%	0.00%	33.33%
Robotic Process Automation	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%

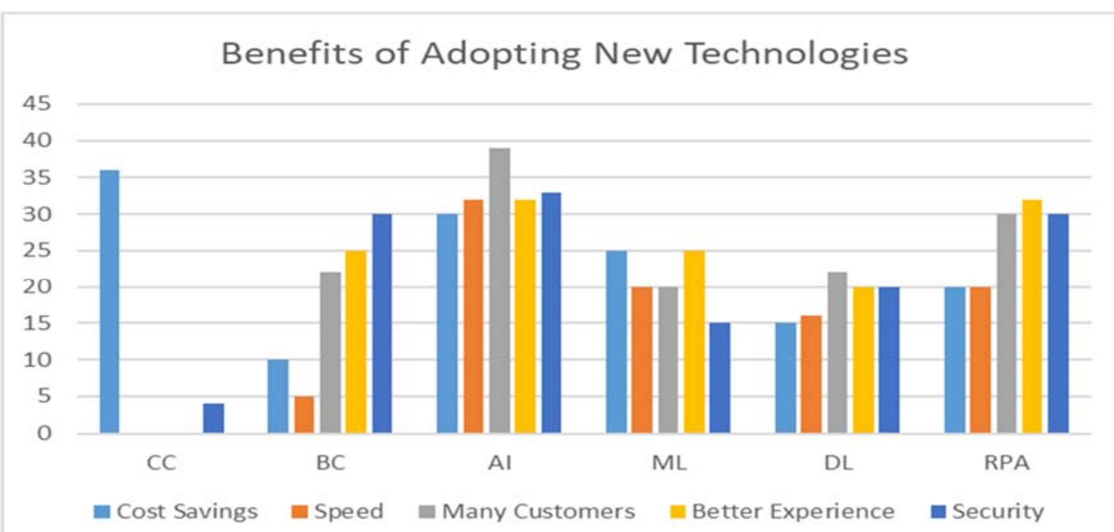
For cloud computing, respondents explained that it is used for accessing data and carrying out remote activities as opposed to providing core banking and other services. AI, ML and DL is also used in predictive analytics and generating reports.

On Question 3, the responses were summarized as in Table 4.7 and Figure 4.4:

Table 4.7 Benefits of adopting various technologies.

	CC	BC	AI	ML	DL	RPA
Cost Savings	36	10	30	25	15	20
Speed	0	5	32	20	16	20
Many Customers	0	22	39	20	22	30
Better Experience	0	25	32	25	20	32
Security	4	30	33	15	20	30

Figure 4.4 benefits of adopting new technologies



The respondents explained that cloud computing enables hosting of data and other activities at an affordable cost and efficient manner. However, for those who adopted other technologies, the main advantage is the ability to access many customers and improve customer experience. For example, using AI to score and determine the loan limits for customers, with a faster response time provided positive feedback from customers.
The respondents highlighted additional benefits of some of the technologies but more specifically for Artificial intelligence; risk management, faster automation and adaptation and partnerships with other organizations, such as Safaricom for mpesa.

On Question 4 ranking the benefits of adopting new technologies is given in Table 4.8:

Table 4.8 Ranking of the benefits of adopting new technologies

Benefit	Score	Rank
Cost savings due to efficiency	4.62	2
Speed of service delivery	4.00	5
Increased customer base	5.00	1
Better customer experience	4.13	4
Improved security	4.21	3

Table 4.8 highlights that MFBs and COMFIs will give priority to new technologies to the extent that it increases the customer base, followed by cost savings.
On question 5, the summary from the respondents was summarized in Table 4.9 and Figure 4.5.

Table 4.9 Summary of the challenges of adopting new Technologies

	CC	BC	AI	ML	DL	RPA
Cost	28	15	20	20	22	30
Poor Infrastructure	0	25	15	10	10	34
Lack of Knowledge	10	15	10	15	15	30
Risk	30	5	25	20	22	10

Strict Regulation	25	15	20	15	10	5

Figure 4.5 Challenges of Adopting New Technologies

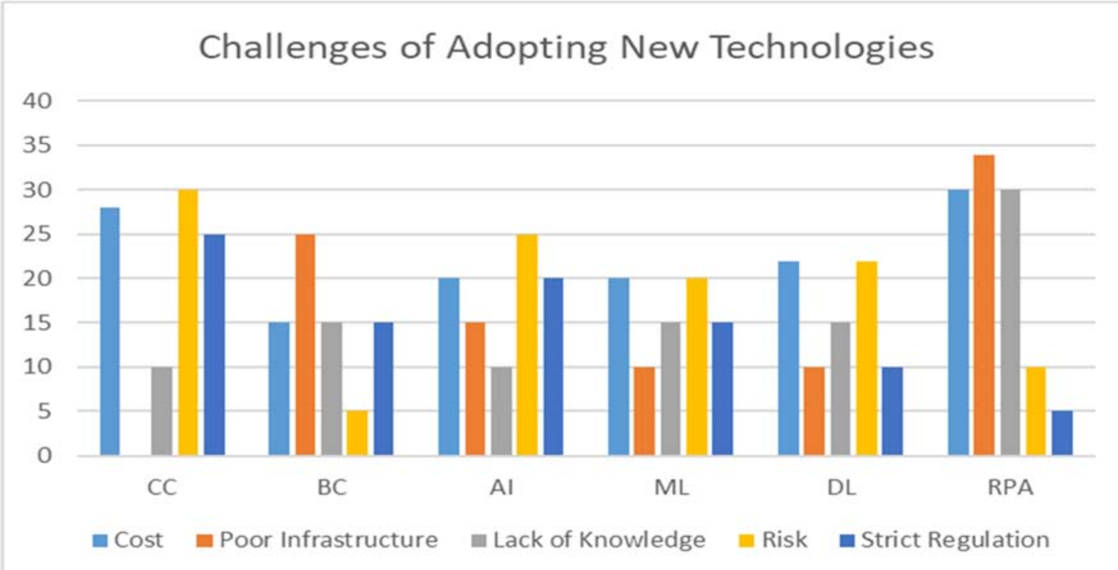


Table 4.9 and Figure 4.5 highlight that for cloud computing and Artificial intelligence, the major challenge is risk associated with outsourcing the data managements and other services. Challenges for blockchain and Robotic Process Automation is infrastructure.

Other challenges that MFBs and COMFIs in adopting new technologies revolved around ensuring compliance with new data protection laws and privacy, some of the systems in place are very difficult to replace (legacy systems), and managing changes associated with new technologies. Many employees fear losing their jobs, when a new technology is proposed or some processes are automated.

Table 4.10 provides a summary of responses to Question 6, ranking the challenges to adopting new technologies:

Table 4.10 Ranking of challenges of adopting new technologies.

Challenge	Score	Rank
Cost	5.00	1
Poor Infrastructure	2.56	5
Lack of Knowledge	3.18	3
Risk	4.38	2
Strict regulation	3.13	4

As expected, costs of adopting to new technologies is an issue. A respondent explained that a major risk for MFBs and COMFIs is to incur high acquisition and installation costs of new technology and then it has to be replaced due to innovations. The next cost is the risk associated with new technologies stemming from disrupting current operations and processes, those associated with cybercrime, and compliance with regulatory requirements.

On question 7, the ranking the importance of these new technologies in aiding MFBs and COMFIs in financial inclusion is summarized in Table 4.11.

Table 4.11 Ranking the importance of new technologies in Financial Inclusion

Technology	Score	Rank
Cloud Computing -CC	4.38	4
Block Chain - BC	2.54	6
Artificial Intelligence - AI	4.92	1
Machine Learning - ML	4.44	3
Deep Learning -DL	4.31	5
Robotic Process Automation - RPA	4.54	2

Overall, the respondents ranked AI as the best technology for financial inclusion. Despite not adopting Robotic Process Automation, the respondents ranked RPA as the second best. However, block chain technology is the last in terms of ranking. Participants provided additional comments about use of technology in financial inclusion, and major points noted were as follows:

-MFBs and COMFIs respondents reiterated the importance of new technologies, having been able to access a significant part of the population, with many Kenyans having access to smart phones. However, the population is more focused on using smart phones and other technologies for borrowing as opposed to savings and accessing other services. This has meant that the use of technology to provide services other than lending is not beneficial.

-New technologies, especially AI has on the one hand reduced the need to invest in buildings and other physical resources, and hence the branch network. However, this has also left out a number of potential borrowers, especially those who are slow to accept new services offered through technology.

-New technologies have improved collaboration across different organizations from the regulators like central banks, internet service providers and other like Safaricom, credit reference bureau and even competitors. However, there are many unethical practices by various players in the industry in the use of technology. For example, the listing of borrowers, even after they have repaid the initially defaulted loans. This means that technology is available, but it takes time to update data real time and is open to abuse by various players.

-Despite advancements in technology, access to reliable and affordable internet is a challenge for current and potential customers. Access to affordable and reliable internet will contribute to continuous technological advancements and financial inclusion.

4.2.2.2 Bivariate Analysis – Correlations of variables

Given that all organizations have adopted AI, this section presents pairwise correlations, to highlight relationships between the variables for analysis.

Table 4.12 provide the pairwise correlations for technology adoption.

Table 4.12 Correlation of new technology adoption

	CC	*BC*	*ML*	*DL*	*RPA*
CC	1.000				
BC	0.634*	1.000			
ML	-0.122	0.170	1.000		
DL	0.410*	0.446	0.062	1.000	
RPA	0.326*	0.522	0.071	0.103	1.000
*5% Significance					

Table 4.12 indicates that there is a positive and significance association between cloud computing and blockchain, deep learning and robotic process automation.

Table 4.13 provides summary of variables influencing adoption of the various technologies.

Table 4.13 Correlation of new technology adoption and other factors

	CC	*BC*	*ML*	*DL*	*RPA*
BS	-0.180	-0.003	0.309	0.093	-0.084
ROE	0.039	-0.216	-0.150	-0.130	-0.150
NPL (Sh.000)	0.433*	0.561	-0.146	0.431*	0.288
CAR	0.415*	0.326	-0.239	0.158	0.218
LR	-0.059	-0.130	0.294	-0.085	0.013
MFB	0.383*	0.702	-0.060	0.424	0.386
SIZE-A (Sh.000)	0.438	0.581	-0.159	0.444	0.318
SIZE-E	0.076	0.170	-0.211	0.140	0.218
SIZE-I (Sh.000)	0.441*	0.459	-0.133	0.442*	0.288
SIZE - B	0.353*	0.514	-0.220	0.266	0.421*
AGE	-0.494*	-0.1457	0.13006	-0.088	-0.07
*5% Significance					

According to Table 4.13, cloud computing is positively associated with poor asset quality, capital adequacy, and size as measured by interest income. In addition, MFB will likely adopt cloud computing compared with COMFIs, while young organizations will adopt cloud computing compared with older ones. Deep learning is positively associated with poor asset quality, size as measured by interest and Robotic process automation is associated with the number of branches.

Table 4.14 summarizes the pairwise correlations for the rest of the variables.

Table 4.14 Correlation of various company variables

	BS	*ROE*	*NPL*	*CAR*	*LR*	*MFB*	*SIZE-A*	*SIZE-E*
BS	1.000							
ROE	-0.301	1.000						
NPL	-0.008	-0.102	1.000					
CAR	-0.106	0.025	0.017	1.000				
LR	0.118	0.246	-0.174	-0.150	1.000			
MFB	-0.125	-0.107	0.561*	0.360	-0.125	1.000		
SIZE-A	-0.017	-0.104	0.997*	0.037	-0.154	0.584	1.000	
SIZE-E	0.123	-0.149	0.562*	-0.181	0.035	0.253	0.572*	1.000
SIZE-I	-0.028	-0.069	0.891*	0.007	-0.030	0.472	0.899	0.539*
SIZE - B	-0.095	-0.156	0.777*	0.017	-0.066	0.598*	0.801*	0.772*
AGE	0.277	-0.304	0.087	-0.428	-0.024	0.012	0.086	0.107
*5% Significance								

Table 4.14 indicates that organizations with poor asset quality i.e. higher levels of non-performing loan will likely be Microfinance Banks and large ones. Meanwhile, organizations having more branches will likely be MFBs, more assets and also many employees.

4.2.2.3 Multivariate Analysis – Factors influencing adoption of new technologies

Since all the organizations have adopted some form of Artificial Intelligence, the logistic regression model was not applied to AI. Tables 4.15 to Table 4.19 summarize the results from the models together with the diagnostic results.

Table 4.15 Summary Multivariate output for cloud computing.

CC - Cloud Computing	**Coef.**	**St.Err.**	**t-value**	**p-value**	**Sig.**
Governance					

Board Size	-1.422	2.684	-0.53	0.596	
Financial Metrics					
Profitability (ROE)	-0.282	0.418	-0.558	0.417	
Asset Quality (Ln NPL)	0.811	0.584	1.158	0.138	
Capital Adequacy (CAR)	-0.637	0.495	-1.075	0.165	
Liquidity (LR)	-0.094	0.190	-0.408	0.518	
Organization					
MFB	-3.052	1.372	-2.22	0.026	**
Other Variables					
Size - Assets (Ln Assets)	-0.338	0.501	-0.67	0.5	
Size - Employees	0.973	0.701	1.39	0.165	
Size - Interest (Ln Interest)	-0.764	0.594	-1.29	0.198	
Size - Branches	-0.113	0.228	-0.49	0.622	
Age	4.317	2.153	2.01	0.045	**
Constant	6.255	4.715	1.33	0.185	
Mean dependent var	0.821		SD dependent var		0.756
Pseudo r-squared	0.286		Number of obs		39
Chi-square	23.626		Prob > chi2		0.001
Akaike crit. (AIC)	74.896		Bayesian crit. (BIC)		88.205
*** p<.01, ** p<.05, * p<.1					

Table 4.15 shows that only MFBs and those older organizations will likely adopt cloud computing. This contradicts the correlation analysis.

NB)

1.The mean dependent variable describes the outcome of this stochastic event with a density function (a function of cumulated probabilities ranging from 0 to 1). A cut point (e.g., 0.5) can be used to determine which outcome is predicted by the model based on the values of the predictors.

2. Pseudo – R squared is the Cox and Snell's R-Square that imitates multiple R-Square based on 'likelihood', but its maximum can be (and usually is) less than 1.0, making it difficult to interpret. It is indicating that 28.6 % of the variation in the dependent variable is explained by the logistic model.

3. The likelihood ratio chi-square is used to evaluate if the logistic model is better than a model with no predictors i.e. a null model. The current model having a likelihood ratio chi-square of 23.626 with a p-value < 0.001 tells us that our model as a whole fits significantly better than a null model.

4. The Akaike information criterion (AIC) is a mathematical method for evaluating how well a model fits the data it was generated from. In statistics, AIC is used to compare different possible models and determine which one is the best fit for the data. The best-fit model according to AIC is the one that explains the greatest amount of variation using the fewest possible independent variables. The smaller the AIC value (74.896) compared with Bayesian critical (88.25), the better the model fit.

Table 4.16 Summary Multivariate output for Blockchain

BC - Block Chain	**Coef.**	**St.Err.**	**t-value**	**p-value**	**Sig.**
Governance					
Board Size	-2.603	2.333	-1.12	0.265	
Financial Metrics					
Profitability (ROE)	0.099	0.620	0.176	0.961	
Asset Quality (Ln NPL)	0.562	0.762	0.814	0.507	
Capital Adequacy (CAR)	-0.428	0.622	-0.759	0.541	
Liquidity (LR)	-0.196	0.298	-0.726	0.562	
Organization					
MFB	-16.261	1842.558	-0.01	0.993	
Other Variables					
Size - Assets (Ln Assets)	0.09	0.564	0.16	0.874	
Size - Employees	0.511	0.693	0.74	0.461	
Size - Interest (Ln Interest)	-0.389	0.565	-0.69	0.492	
Size - Branches	-0.178	0.271	-0.66	0.511	
Age	2.096	1.565	1.34	0.18	
Constant	0.345	5.709	0.06	0.952	
Mean dependent var	1.026		SD dependent var		0.778
Pseudo r-squared	0.357		Number of obs		39
Chi-square	30.233		Prob > chi2		0
Akaike crit. (AIC)	70.411		Bayesian crit. (BIC)		83.719

*** p<.01, ** p<.05, * p<.1					

Table 4.16 indicates that none of the variables are significant in the adoption of blockchain technology. The Pseudo – R squared indicates that 35.7 % of the variation in the dependent variable is explained by the logistic model. This model has a likelihood ratio chi-square of 30.626 with a p-value < 0.001 tells us that our model as a whole fits significantly better than a null model. The Akaike information criterion (AIC) value of (70.411) compared with Bayesian critical (83.719), the better the model fit.

Table 4.17 Summary Multivariate output for Machine Learning.

ML - Machine Learning	Coef.	St.Err.	t-value	p-value	Sig.
Governance					
Board Size	3.02	1.818	1.66	0.097	*
Financial Metrics					
Profitability (ROE)	-0.036	0.302	-0.086	0.646	
Asset Quality (Ln NPL)	0.065	0.426	0.107	0.627	
Capital Adequacy (CAR)	0.095	0.307	0.221	0.541	
Liquidity (LR)	-0.129	0.129	-0.714	0.225	
Organization					
MFB	-0.114	0.74	-0.15	0.877	
Other Variables					
Size - Assets (Ln Assets)	-0.051	0.423	-0.12	0.904	
Size - Employees	0.091	0.596	0.15	0.878	
Size - Interest (Ln Interest)	0.133	0.43	0.31	0.758	
Size - Branches	-0.18	0.18	-1	0.315	
Age	0.374	1.224	0.31	0.76	
Constant	-0.599	5.047	-0.12	0.906	
Mean dependent var	0.462		SD dependent var		0.505
Pseudo r-squared	0.078		Number of obs		39
Chi-square	4.195		Prob > chi2		0.241
Akaike crit. (AIC)	57.639		Bayesian crit. (BIC)		64.293
*** p<.01, ** p<.05, * p<.1					

Table 4.17 indicates that only the board size is associated with adoption of machine learning. However, this model diagnostics shows the models is somehow, but not significantly string for forecasting. The Pseudo – R squared is indicating that 7.8 % of the variation in the dependent variable is explained by the logistic model. This model has a likelihood ratio chi-square of 4.195 with a p-value > 0.241 tells us that our model as a whole fits poorly compared with a null model. The Akaike information criterion (AIC) value of (57.639) compared with Bayesian critical (64.293), indicating a better, but not highly model fit.

Table 4.18 Summary Multivariate output for Deep Learning

DL - Deep Learning	Coef.	St.Err.	t-value	p-value	Sig.
Governance					
Board Size	4.58	3.775	1.21	0.225	
Financial Metrics					
Profitability (ROE)	1.082	0.744	0.580	0.058	*
Asset Quality (Ln NPL)	4.518	2.857	0.632	0.046	
Capital Adequacy (CAR)	4.633	2.718	0.680	0.035	*
Liquidity (LR)	-1.567	0.968	-0.648	0.042	*
Organization					
MFB	2.173	0.92	2.36	0.018	**
Other Variables					
Size - Assets (Ln Assets)	2.706	1.86	1.45	0.146	
Size - Employees	11.295	7.143	1.58	0.114	
Size - Interest (Ln Interest)	11.582	6.796	1.7	0.088	*
Size - Branches	-3.918	2.42	-1.62	0.105	
Age	-1.647	2.737	-0.6	0.547	
Constant	-8.011	9.524	-0.84	0.4	
Mean dependent var	0.513		SD dependent var		0.644
Pseudo r-squared	0.636		Number of obs		39
Chi-square	44.052		Prob > chi2		0
Akaike crit. (AIC)	45.215		Bayesian crit. (BIC)		61.851
*** p<.01, ** p<.05, * p<.1					

Table 4.18 indicates that adoption of deep learning technology is positively associated with Profitability and Capital adequacy. In addition, MFBs will likely adopt deep learning and those earning a higher interest. However, those organizations having a poor liquidity will not adopt deep learning technology. The Pseudo – R squared is indicating that 63.6 % of the variation in the dependent variable is explained by the logistic model. This model has a likelihood ratio chi-square of 44.052 with a p-value < 0.001 tells us that our model as a whole fits significantly better than a null model. The Akaike information criterion (AIC) value of (45.215) compared with Bayesian critical (61.851), the better the model fit.

Table 4.19 Summary Multivariate output for Robotic Process Automation

RPA - Robotic Process Automation	Coef.	St.Err.	t-value	p-value	Sig.
Governance					
Board Size	-2.204	2.125	-1.04	0.3	
Financial Metrics					
Profitability (ROE)	0.276	0.481	0.317	0.314	
Asset Quality (Ln NPL)	0.211	0.378	0.311	0.321	
Capital Adequacy (CAR)	4.613	5189.389	0.000	0.555	
Liquidity (LR)	7.065	1576.522	0.000	0.398	
Organization					
MFB	96.494	20162.28	0	0.996	
Other Variables					
Size - Assets (Ln Assets)	0.496	0.865	0.57	0.566	
Size - Employees	0.379	0.681	0.56	0.578	
Size - Interest (Ln Interest)	8.303	9340.9	0	0.999	
Size - Branches	17.663	3941.305	0	0.996	
Age	0.128	1.361	0.09	0.925	
Constant	1.158	11.706	0.1	0.921	
Mean dependent var	0.615		SD dependent var		0.673
Pseudo r-squared	0.13		Number of obs		39
Chi-square	9.644		Prob > chi2		0.291
Akaike crit. (AIC)	84.412		Bayesian crit. (BIC)		101.05
*** p<.01, ** p<.05, * p<.1					

Table 4.19 indicates that none of the variables is associated with robotic process automation technology adoption. However, this model diagnostics shows the models is somehow, but not significantly strong for forecasting. The Pseudo – R squared is indicating that 13 % of the variation in the dependent variable is explained by the logistic model. This model has a likelihood ratio chi-square of 9.644 with a p-value > 0.241 tells us that our model as a whole fits poorly compared with a null model. The Akaike information criterion (AIC) value of (84.412) compared with Bayesian critical (101.05), indicating a better, but not highly model fit.

4.3 Summary

Chapter Four has presented the results and findings of the study. The section has presented the levels of adoption of technologies, services, benefits and challenges of adopting new technologies, and an analysis of factors influencing the adoption of the new technologies.

CHAPTER FIVE: DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

Chapter Five is the last chapter of this thesis. Chapter One introduced the study, whose focus is on the use of technologies in financial inclusion by Microfinance Banks (MFBs) and Credit Only Microfinance institutions (COMFIs). Micro Finance Institutions (MFIs) engage in relatively small financial transactions using various methodologies to serve low-income households, micro enterprises, small scale farmers, and others who lack access to traditional banking services, CBS (1999). COMFIs usually provide credit to small and medium sized entities and individuals without receiving deposits. However, a few of the clients save with them. Financial inclusion is where business entrepreneurs and individuals access financial products and services with the view to satisfying their needs and those of their clients (Sharma, 2016). It has to do with saving, making, and receiving payments, transacting, receiving credit, and insurance (Atkinson & Messy, 2013).

The general objective of this study was to evaluate the application of new technologies in financial inclusion by microfinance banks and credit only institutions. The specific objectives were first to assess the extent to which microfinance banks and credit only institutions use new technologies in financial inclusion. Secondly, to establish organizational factors that influence the use of new technologies in financial inclusion by microfinance banks and credit only institutions. Finally, to evaluate stakeholder perspectives on the relevance of new technologies in financial inclusion.

Chapter Two posited the theories underpinning the study being the Diffusion of Innovation Theory (DOI) and Financial Intermediation Theory (FI). The chapter presented gaps in empirical literature. Chapter Three provided the research methods. The study was based on both positivist and postpositivist research philosophies, using the mixed methods (both quantitative and qualitative approaches). The study targeted all the 13 MFBs listed by Central Bank of Kenya and 34 COMFIs listed by AMFI-K by end of 2022. However, only 39 responses were received. The study used both primary and secondary data. Primary data was collected using an online questionnaire, while secondary data collected from annual reports of various MFBs and COMFIs. To determine, organizational factors influencing adoption of new technologies, the multinomial logistic regression was applied. Chapter Four presented the results and findings. Chapter Five discusses the results and findings, provides conclusions, limitations of the study and recommendations for further studies.

5.2 Discussions

5.2.1 Objective 1 – Level of Technology Adoption

According to findings, all organizations have adopted Artificial intelligence, Machine Learning is the next popular technology, then blockchain and cloud computing. However, many respondents acknowledged they are considering incorporating aspects of robotic process automation technology, even though it is the least adopted. AI is used in most of Receiving Deposits, Lending, Payment Services, Money Transfers and Insurance. For cloud computing, is used for accessing data and carrying out remote activities as opposed to providing core banking and other services.

These findings support and contribute to empirical literature in various ways. First on the findings support those of Misra and Doneira (2018), regarding the adoption of cloud computing, and contribute to empirical literature on the extent and use of application of cloud computing to MFBs and COMFIs.

The findings also support those of Wanke et al. (2022) on the relevance of blockchain technology. The study has established that blockchain technology is popular with MFBs and COMFIs and is used mainly for keeping secured records of lending and cash transfers. Unlike in the study of Odoh (2018) on the use of artificial intelligence in record keeping by Nigerian microfinance banks, this study contributes to knowledge having established that AI is the only technology that has been adopted by MFBs and COMFIs. AI is also used across all the services.

Despite the benefit of Robotic Process Automation as argued by Barnet (2015), this technology is not popular with MFBs and COMFIs as per the findings. However, most organizations are considering adopting RPA.

5.2.2 Objective 2 – Factors influencing adoption of new technologies

The current study contributes to empirical literature in several ways. First, board size is associated with adoption of machine learning technology only. Secondly, profitable firms, those with more nonperforming loan and those with sufficient capital adequacy will likely adopt deep learning. Third, MFBs banks will least likely adopt cloud computing as compared with COMFIs. On the contrast, MFBs will likely adopt deep learning, as compared with COMFI. Finally, older organizations will likely adopt cloud computing as compared to the younger ones.

5.2.3 Objective 3 – Management's perspectives on the relevance of new technologies in financial inclusion

The study has contributed to empirical literature in various ways based on the feedback from stakeholders.

MFBs and COMFIs adopt new technologies to increase the customer base and for cost savings. This finding supports the empirical studies of Mwela (2014) and Sowmya & Reddy (2018), but highlights the main motivation for adoption of new technology for enhanced financial inclusion i.e. reaching as many customers as possible.

MFBs and COMFIs ranked the cost of adopting new technologies as the main barrier. As explained in the background chapter, MFBs and COMFIs may not have significant resources when compared with the banks and other players in financial services. These findings support Rozzani and Rashidah (2013), but with an additional perspective that MFBs and COMFIs are hesitant to adopt new technologies due to the risk of technology becoming obsolete as a result of technological innovations. In addition, the study established that MFBs and COMFIs also want to avoid the risk associated with new technologies stemming from disrupting current operations and processes, those associated with cybercrime, and compliance with regulatory requirements.

Overall, the respondents ranked AI as the best technology for financial inclusion. This supports Fernandez (2019), who argued about the role of artificial intelligence (AI) in transforming the landscape of financial services by revolutionizing the way transactions are processed, analyzed, and executed. The study has further extended the status of the rest of the technologies by MFBs and COMFIS. For example, even though majority of the respondents are yet to adopt Robotic Process Automation, the respondents ranked RPA as the second-best technology for financial inclusion, but block chain technology is the last in terms of ranking.

In line with Mwela (2014) and Sowmya and Reddy (2018) MFBs and COMFIs have been able to access a significant part of the population because many Kenyans possess smart phones, but unfortunately the customers have focused on borrowing as opposed to saving and using other services. This will likely lead to adoption of new technologies that aim to enhance the borrowing experience for customers or possibly, or just reduce the motivation to adopt new technologies.

Met at al. (2020), explained that RPA and other technologies help financial institutions improve customer experiences by providing faster and more accurate responses to inquiries. Based on respondents' feedback, new technologies, have on the one hand reduced the need to invest in buildings and other physical resources, and hence the branch network. However, this has also left out potential borrowers, especially those who are slow to accept new services offered through technology. In addition, MFBs and COMFIs have a challenge providing personalized services to customers and even undertake financial literacy.

New technologies have improved collaboration across different organizations from the regulators like central banks, internet service providers and other like Safaricom, credit reference bureau and even competitors. According to Danilesson et al. (2017), this can reduce the likelihood of financial losses, protect investors, and ensure the stability of the financial system. However, respondents have noted that some participants in the system abuse the new technologies and information sharing. This can hinder the progress made in using technology for financial inclusion.

Finally, despite the acknowledgement by MFBs and COMFIs on the role of role of new technologies in financial inclusion, improvement and adoption of new technologies will be challenged due to lack of reliable and affordable internet services. This confirms the argument by Ulwodi and Muriu (2017), on the challenges of new technology, especially from the perspective of low-cost technologies.

5.3 Conclusion

This study has provided empirical evidence on the importance and application of new technologies adoption for financial inclusion by MFBs and COMFIs. Artificial intelligence is the leading technology by MFBs and COMFIs, has this has been adopted by all organizations. Despite Robotic Process being the least adopted, it is being considered by majority of the organization for adoption. The main motivation of adopting new technologies is to increase the customer base (enhance financial inclusion). However, cost of adopting new technologies is a major barrier, given the resource constraints that MFBs and COMFIs face. In terms of theoretical framework, the DOI model integrates three major components, namely, the characteristics of the adapter, the characteristics of the innovation, and the innovation-decision process.

This study has also extended empirical literature on factors influencing adoption of new technologies. First board size is associated with adoption of machine learning technology only. Secondly, profitable firms, those with more nonperforming loan and those with sufficient capital adequacy will likely adopt deep learning. Third, MFBs banks will least likely adopt cloud computing as compared with COMFIs. On the contrast, MFBs will likely adopt deep learning, as compared with COMFI. Finally, older organizations will likely adopt cloud computing as compared to the younger ones. Many of the other factors such as size as measured by assets are positive but not significant.

In terms of theoretical framework, the study was anchored on the Diffusion of Innovation Theory (DOI) and Financial Intermediation Theory (FI). The DOI model integrates three major components, namely, the characteristics of the adapter, the characteristics of the innovation, and the innovation-decision process. The study has confirmed the extent of adoption of new technologies (being AI) and various company features influencing adoption of new technologies. Under FI theory, MFB and COMFIS being intermediaries, the study has provided the extent to which new technology is deployed to enable MFBs and COMFIS to become better intermediaries and promote financial inclusion (Swamy & Tulasimala, 2012; Markides, 2014).

5.4 Limitation of the study

Despite attempts to enhance quality of the study, some issues arose in the process that paused a challenge in the conduct and conclusion of the study. However, these were not significant enough to invalidate the findings.

First, the population of MFBs and COMFIs is small with a population of 47 organizations. However, the response rate was sufficient for analysis, given the use of a survey.

Second, there was a challenge in obtaining secondary information for some COMFIs, as they have no legal or statutory requirement to publish the annual report. So, more effort was made for the COMFIs to provide the information in the questionnaire.

Third, even though the initial target respondents were mainly CIOs, not all of them were available to fill out the questionnaire. The list of contact persons were CEOs. Some CEOs forwarded the request, while others decided to fill the questionnaire, to avoid providing any confidential information about the organization. Furthermore, CEOs and CIOs who filled in the questionnaire had to consult the finance department for some of the figures in financial statements, of which a few were therefore estimates.

Fourth, the response time to the questionnaire was slow. Many respondents were initially hesitant to fill in the questionnaire, fearing the information required is competitive. More effort was required in terms of polite reminders on email, phone calls and office visits.

Finally, the multinomial model of analysis has several assumptions, on which the analysis is based on. Key ones include: Observations are independent, mutually exclusive and exhaustive variables, no multicollinearity between independent variables, a linear relationship between continuous variables and the logit transformation of the outcome variable and finally, no outliers or highly influential points. In conducting the analysis, these assumptions, also applied, of which their valuation would have made the analysis difficult to interpret.

5.5 Recommendations for further studies

Given the objectives, the design and the challenges of the study, further studies may widen the scope in various ways. Future studies may consider other financial services organizations, such as insurance companies and Savings and Credit Societies (SACCOS), that aim to increase financial inclusion. In addition, further studies may also look at the customer experience with technology in achieving financial inclusion, for example, the forms of technology preferred for financial inclusion and strategies to improve customer experience. Studies can also consider the role of different participants in promoting the use of technology for financial inclusion, including policy guidelines for technologically supported financial inclusion.

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APPENDICES

Appendix I: Letter of Introduction

Dear Sir/Madam,

RE: Letter of Request for Permission to Collect Data

I am a student pursuing Master of Science in Development Finance at Strathmore University. I am requesting for data to complete my research titled '**ASSESSING THE USE OF NEW TECHNOLOGIES IN FINANCIAL INCLUSION BY MICROFINANCE BANKS AND CREDIT ONLY INSTITUTIONS IN KENYA'.**

The data requested is for academic purposes and the information will be treated with utmost confidentiality.

Yours Sincerely

Wilson Kivati

Student Reg No. 123667

Appendix II: Questionnaire

Instructions

Kindly complete the following questionnaire using the instruments provided for each set of questions. Please tick appropriately or write your answers in the spaces provided.

Confidentiality

All information given shall be treated with strict confidence. No reference will be made to any individual(s) or organization in the report of the study.

Part A: Respondent Details

1. Position in the organization____

2. Duration in the organization____

Part B: Organizations Details

1. Which of the following applies to your organization?

It is a…

Microfinance Bank (MFB) ☐

Credit Only Microfinance Institution (COMFI) ☐

2. Years in operation____

3. Number of Directors on Board____

4. The organization provides the following services:

Receiving Deposits ☐

Lending ☐

Payment Services ☐

Money Transfers ☐

Insurance ☐

Others ☐

Indicate Others below…

____

____

____

____

____

5. In terms of Size indicate the following:

Number of employees as at end of 2022______________________________

Total Interest revenue from lending in 2022______________________________

Total Assets in 2022______________________________

Number of branches in 2022______________________________

6. Other financial performance metrics in 2022

Profit after tax ______________________________

Total Loans______________________________

Nonperforming Loans______________________________

Total Liabilities______________________________

Total Capital____

Capital Adequacy Ratio____

Liquidity Ratio (Total Liquid Assets/Short term Liabilities)____________________

Part C: Use of New technologies in Financial Inclusion

The following are new technologies that are used in financial services:

Technology	**Meaning**
Cloud Computing	Using a network of remote servers hosted on the internet to store, manage, and process data, rather than a local server or a personal computer).
Blockchain	A ledger of decentralized data that is securely shared
Artificial Intelligence	Computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages)
Machine Learning	The use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.
Deep Learning	A type of machine learning based on artificial neural networks in which multiple layers of processing are used to extract progressively higher-level features from data.
Robotics Process Automation	RPA refers to the automation of business processes by digital software robots for repetitive and rule-based work tasks

1. Are the following technologies being applied in the organization:

	Tick applicable √		
	Yes	Not Yet But Being considered	No
Cloud Computing			
Blockchain			
Artificial Intelligence			

Machine Learning			
Deep Learning			
Robotic Process Automation			

2. Which aspects of the business is the technology used?

	Receiving Deposits	Lending	Payment Services	Money Transfers	Insurance	Others
Cloud Computing						
Blockchain						
Artificial Intelligence						
Machine Learning						
Deep Learning						
Robotic Process Automation						

For other types of Services indicate the services

3. Which of the following benefits apply in the adoption of the new technologies:

	Cost savings due to efficiency	Speed of service delivery	Increased customer base	Better customer experience	Improved security	Others
Cloud Computing						
Blockchain						
Artificial Intelligence						
Machine Learning						

Deep Learning						
Robotic Process Automation						

In case of other benefits provide them below:

4. Rank the benefits in order of importance in the adoption of new technologies in terms:

	Very Low	Low	Average	High	Very High
Cost savings due to efficiency					
Speed of service delivery					
Increased customer base					
Better customer experience					
Improved security					
Others					

Provide more details for other benefits:

5. Which of the following are the challenges of adopting and implementing new technologies that the organization is facing?

	Cost	Poor Infrastructure	Lack of Knowledge	Risk	Strict Regulation	Others
Cloud Computing						
Blockchain						
Artificial Intelligence						
Machine Learning						
Deep Learning						
Robotic Process Automation						

Provide more details for other challenges:

6. Rank these challenges from extreme to not at all in terms of adopting new technologies?

	Extremely	Very	Moderately	Slightly	Not at all
Cost					
Poor Infrastructure					
Lack of Knowledge					
Risk					
Strict regulation					

Others					

Provide more details for other challenges:

7. Rank these new technologies in terms of importance in aiding MFBs and COMFIs in promoting financial inclusion:

	Not Important	Slightly Important	Fairly Importan t	Important	Very importan t
Cloud Computing					
Blockchain					
Artificial Intelligence					
Machine Learning					
Deep Learning					
Robotic Process Automation					

Provide a brief explanation of the choice of your answers:

8. Provide any other information that may be relevant for use of new technologies by the MFB or COMFI in financial inclusion. The information may include an outlook of these technologies in financial inclusion, strategies that stakeholders can have in place to promote the use of these technologies.

Provide a brief explanation of the choice of your answers:

Appendix III: Microfinance Banks and Credit Only Institutions

Microfinance Banks as at 2022 - 13

Caritas Microfinance Bank	Remu Microfinance Bank
Century Microfinance Bank	SMEP Microfinance Bank
Choice Microfinance Bank	Sumac Microfinance Bank
Daraja Microfinance Bank	U & I Microfinance Bank
Faulu Microfinance Bank	Uwezo Microfinance bank
Kenya Women Microfinance Bank	
Maisha Microfinance	

Source: Central Bank of Kenya (2022) Website

Credit only microfinance institutions - 34

Eclof Kenya	Habitat for Humanity International
Vision Fund Kenya Limited	Real People Limited
Bimas	Neema Health Educational & Empowerment
Letshegi Kenya	Ushindi Bora
Zenka Finance	Hand in hand Eastern Africa
Yehu Microfinance Trust	Nyali Capital
Jitegemea Credti Scheme	Premier Credit
Fincredit Services	Moneyworth Investment
Juhudi Kilimo Company	Hazina Development Trust
Musoni Kenya	Springboard Capital
Select Management Services	Progressive Credit
Greenland Fedha Limited	Longitude Finance
Platinum Credit	Jiweze
Asa	Kipepeo
Diversity Microcredit	My Credit
Pawdep	Momentum Credit
Weighbridge Ventures	

Association of Microfinance Institutions - Kenya Website (2023)

Appendix IV: Ethical approvals

Strathmore
UNIVERSITY

28th September 2023

Mr Kivati Wilson,
wilson.kivati@strathmore.edu

Dear Mr Kivati,

<u>RE: Assessing the Use of New Technologies in Financial Inclusion by Microfinance Banks and Credit Only Institutions in Kenya</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1852/23**. The approval period is from **28th September 2023 to 27th September 2024.**

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

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