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Effect of company specific characteristics on the adoption of emerging technologies in finance functions: case of non-financial companies listed in Kenya.

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EFFECT OF COMPANY SPECIFIC CHARACTERISTICS ON THE ADOPTION OF EMERGING TECHNOLOGIES IN FINANCE FUNCTIONS: CASE OF NON-FINANCIAL COMPANIES LISTED IN KENYA

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DECLARATION

I declare that this work 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

Over the past decade, corporations have taken advantage of low-cost and efficient technologies to automate their finance departments in a bid to gain a competitive advantage through lowering administrative overheads, improving risk management, and ensuring that data that is required for decision-making by business leaders is provided on a real-time basis to ensure quick decision making. The study aimed to assess the level of usage of emerging technologies in the finance function of listed non-financial companies in the Nairobi Securities Exchange (NSE), identify company features and the type of emerging technologies adopted, and identify opportunities for the application of emerging technologies and challenges that hinder the adaption of the emerging technologies. Leveraging the Diffusion of Innovation Theory and Technology Organization Environment Theory, data on company characteristics was collected from primary data sources through a questionnaire administered to the Chief Finance Officers and secondary data from audited financial statements of 34 listed non-financial companies to assess the influence of company characteristics on the adoption of emerging finance technologies through the use of a binary logistic regression model. The findings indicated that the level of usage of emerging technologies in the finance function of listed non-financial companies in the NSE is at the initial phase of development with 21.7% of the companies having adopted the use of emerging technologies. The binary logistic regression model analysis found that company profitability, ownership concentration and ownership concentration and CFO tenure had a negative, relationship with the adoption of emerging finance technologies whilst company liquidity, size age, board independence, number of employees in the finance department, and CFO age had a positive relationship with the adoption of emerging finance technologies and none of the independent variables had a significant relationship with the adoption of the emerging finance technologies. The study also revealed a significant lack of enthusiasm among listed non-financial companies to identify opportunities for adopting emerging finance technologies, citing challenges such as insufficient IT infrastructure, limited awareness of functionalities, and a skills gap, and recommends that Companies invest in foundational tools and necessary talent to reap the potential benefits. This research contributes to the literature on technological innovation and breaks new ground by focusing on non-financial companies listed on the NSE.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BI	Board Independence
CA	Company Age
CFA	CFO Age
CFO	Chief Finance Officer
CFT	CFO Tenure
DOI	Diffusion of Innovation
EF	Number of employees in Finance Function
NSE	Nairobi Securities Exchange
OC	Ownership Concentration
OM	Company Profitability
QR	Company Liquidity
RPA	Robotic Process Automation
TA	Company Size
TOE	Technology Organization Environment

DEDICATION

I dedicate this work to my beloved Wife, Salome, and our son, Ethan, your unwavering support and encouragement was my inspiration.

CHAPTER ONE

INTRODUCTION

1.1. Background of the study

Over the past decade, corporations have started the transformation of their finance departments by taking advantage of today's low-cost, efficient emerging technologies to automate the finance departments in a bid to gain a competitive advantage by lowering their administrative overheads and other efficiencies gained from automation.

According to Plaschke, et al. (2018), emerging technologies can fully automate 42 percent of the finance function activities and mostly automate a further 19 percent leading to changes in organizational structures, redefined roles, and ultimately to inevitable layoffs.

Zhang et al. (2020) performed a study on the application of emerging technologies by the Big Four Accounting Firms and concluded that the integration of emerging technologies in the finance function had resulted in significant changes to the accounting profession such as the introduction of new accounting procedures, reduction in accounting errors, increased efficiency, and the transformation of the accounting career structure.

According to Kaya et al. (2019), Emerging Finance Technologies will disrupt the accounting profession resulting in accounting operations being automated and finance professionals will focus on more strategic accounting management in the future.

Lacity et al. (2015) performed a case study on Robotic process automation at Telefonica O2, a telecommunications services provider. The Company was one of the early adopters of RPA and the study highlighted that as of April 2015, the Company had automated over 35 percent of its transactions in 15 core processes which included SIM swaps, credit checks, order processing, customer reassignment, and customer data updates, resulting in radically transforming the back offices to deliver lower cost whilst improving service quality, increasing compliance, and decreasing delivery time.

Several empirical studies have concluded that the emerging technologies will result in significant disruption to the finance and accounting profession, this study sought to investigate the effect of company specific characteristics on the adoption of emerging technologies in the finance function of listed non-financial companies in the Nairobi Securities Exchange (NSE). Emerging technologies include software and other technologies that have been introduced to automate traditional forms of finance in a bid to introduce efficiencies such as cost reduction, streamline compliance, and improve the decision-making process.

The study reviewed four emerging technologies which include Robotic Process Automation ("RPA"), Machine Learning, Artificial Intelligence ("AI"), and Blockchain. Section 1.1.1 presents a brief introduction to these emerging technologies and their applications in Finance. By leveraging the Technology Organization Environment (TOE) theory and the Diffusion of Innovation theory (DOI), the study focused on investigating the effect of company specific characteristics on the adoption of emerging technologies in the finance function of listed non-financial companies listed in the NSE. The company specific characteristics were grouped into three dimensions of company financial metrics, namely company profitability, liquidity and size, other company features, namely board independence, ownership concentration and the duration which the company has been listed in the NSE and finance department characteristics, namely the number of employees in the finance function, the Chief Finance Officer (CFO) age and CFO tenure as the independent variables to identify the company features of non-financial companies listed in the NSE that had adopted these emerging technologies in the finance function. Furthermore, the study sought to identify the type of technologies adopted and to enumerate the opportunities that had been identified for the application of the emerging technologies and challenges that hinder the adaption of the emerging technologies by finance departments of non-financial companies listed in the NSE.

1.1.1. Emerging Technologies in Finance

A brief introduction to RPA, AI, Machine Learning, and Blockchain is presented in the section below. The study focused on the adoption of AI, Blockchain, RPA, and Machine Learning in finance functions due to their significant transformative impact amidst the rapidly evolving landscape of emerging technologies. AI offers advanced analytics to enhance decision-making, while blockchain ensures transparent and secure transactions. RPA streamlines processes, leading to reduced costs, and machine learning facilitates data-driven decision-making. By concentrating on these technologies, the study aimed to comprehensively explore their adoption dynamics and implications within the finance function to provide insights for navigating the evolving landscape of emerging technologies in the finance function.

1.1.1.1. Robotic Process Automation (“RPA”)

According to Lacity, et al., (2015), 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. 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”. Kaya, et al. (2019), explained that RPA technologies can be used to send e-mails, record data, and complete spreadsheets and can therefore be used to automate processes ranging from simple data processing tasks such as data entry and processing to bank statement reconciliation, and payment processing to complex tasks such as budgeting and forecasting and financial planning and analysis. Kaya, et al. (2019) concluded that automation through RPA allows finance professionals to pay attention to activities that generate more value for the organization.

1.1.1.2. Artificial Intelligence (AI)

Vassilopoulos (2010) described 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. Artificial intelligence (AI) is the programming human intelligence in machines to think, learn and some extent act like humans to perform tasks human tasks like decision-making. Berdiyeva et al. (2021) explained that AI can be applied in accounting and finance in a variety of ways such as optimizing budgeting and forecasting processes using algorithms to scrutinize historical data and identify patterns that can be incorporated to improve forecasts. AI can also be used to detect fraudulent activity by using algorithms to monitor transactions and flag unusual patterns.

1.1.1.3. Machine Learning

According to Zhang et al. (2020), "machine learning can be described as the ability of computers to operate without being explicitly programmed". Kapoor et al. (2021) explained that machine learning is used to improve various areas of the finance industry such as payment transactions, fraud detection, forecasting of returns, portfolio management and financial modeling. Emerson et al. (2020) further noted that Machine Learning applies a series of statistical techniques to conduct self-learning activities from a dataset to perform specified tasks without being programmed to do so and can be used to improve processes such as fraud detection and processing of payments across the finance function.

1.1.1.4. Blockchain

Yu et al. (2018) defines blockchain as an electronic ledger that records transactions and information. Desplebin et al. (2021) outlined how blockchain technology enables the creation and use of a public transaction registry that is arranged chronologically. According to The Institute of Chartered Accountants in England and Wales, (2018), Blockchain technology, which transfers asset ownership while keeping a record of precise financial data, has the potential to improve the accounting industry by lowering ledger maintenance and reconciliation costs and offering complete assurance regarding asset ownership and history. Decentralized financial systems that enable peer-to-peer transactions without the use of middlemen like banks are also made possible by blockchain technology.

1.1.2. Nairobi Securities Exchange

The Nairobi Securities Exchange consists of 66 listed companies and the equities market consists of three market segments that include The Main Investment Market Segment, The Alternative Investment Market Segment, and The Growth Enterprise Market Segment. The 66 publicly traded companies have been classified into 13 industries which include Agricultural, Automobiles and Accessories, Banking, Commercial and Services, Construction & Allied, Energy & Petroleum, Insurance, Investment, Investment Services, Manufacturing & Allied, Telecommunications, Real Estate Investment Trust, and Exchange Traded Funds.

1.2. Problem Statement

Finance organizations own most of the data that is required by business leaders to make critical decisions since they perform a wide range of activities ranging from the collection and analysis of data to reporting and storing the data for future use. Agarwal and Shroff (2021) noted that finance functions have a challenge in obtaining data insights because of cross cutting systems that are manually analysed in spreadsheets which presents significant problems for finance functions. Firstly, the presence of cross-cutting systems results in data fragmentation, making it difficult to consolidate information and gain a comprehensive view of financial data. Secondly, relying on manual analysis conducted in spreadsheets introduces inefficiencies and increases the likelihood of errors, hindering productivity and accuracy. Thirdly, the risk of obtaining inaccurate insights arises due to data fragmentation and manual analysis, potentially leading to faulty conclusions and decisions based on unreliable information. Furthermore, the manual nature of data analysis and fragmented systems contributes to delays in obtaining insights, impeding timely decision-making and responsiveness to changing business environments. Finally, the lack of agility stemming from these challenges may hinder the organization's ability to adapt to rapidly changing market conditions or emerging trends. The introduction of emerging technologies in finance operations could be a catalyst for competitive advantage by enabling the finance function to provide critical, real-time data to business leaders for quick decision making supported by relevant data.

The study aimed to identify the effect of company specific characteristics on the adoption of emerging technologies in the finance function of listed non-financial companies in the NSE, assess the level of usage of emerging technologies in the finance function of listed non-financial companies in the NSE and identify opportunities for the adoption of emerging technologies and challenges that hinder the adaption of the emerging technologies by finance departments of listed non-financial companies in the NSE. By answering and addressing these research questions, the study aimed firstly in understanding the factors that drive the adoption of emerging financial technologies by listed non-financial companies in the NSE providing insights into the broader trend of digital transformation within the finance function because as more companies adopt emerging technologies, there could be implications for the competitiveness and efficiency of the listed non-manufacturing companies in the NSE and the wider economy. Secondly, the findings of this research aimed at helping policymakers and regulators develop appropriate policies and regulations that would facilitate the adoption of emerging financial technologies, while also mitigating any risks associated with their use. Thirdly investors in the NSE could use the insights from this research to make informed investment decisions because understanding which companies are more likely to adopt emerging financial technologies and which ones are not could be valuable information for investors looking to identify potential winners and losers in the evolving digital landscape of emerging finance technologies.

1.3. Research Objectives

The general objective of this study was to identify the company specific characteristics that influence the adoption of emerging technologies in the finance function of listed non-financial companies in the NSE. The study was guided by the following specific objectives.

(i) To identify the effect of company specific characteristics on the adoption of emerging technologies in the finance functions of listed non-financial companies in the NSE.

(ii) To assess the level of usage and the type of emerging technologies adopted in the finance function of listed non-financial companies in the NSE.

(iii) To identify opportunities for the application of emerging technologies and challenges that hinder the adaption of the emerging technologies by finance departments of listed non-financial companies in the NSE.

1.4. Research Questions

The following were the research questions.

(i) What is the effect of company specific characteristics on the adoption of emerging technologies in the finance functions of listed non-financial companies in the NSE.

(ii) What are the emerging technologies that listed non-financial companies have adopted in their finance function and what is the level of usage of these emerging technologies?

(iii) What opportunities and challenges have listed non-financial companies in the NSE identified for the adoption of emerging technologies in their finance departments?

1.5. Scope of the Study

This study focused on the finance function of listed non-financial companies in the NSE because finance owns most of the data that is required by business leaders to make critical decisions since the function performs a wide range of activities ranging from collection and analysis of data to reporting and storing data for future use. The study focused on listed non-financial companies in the NSE because listed companies can serve as an indicator of trends in emerging technologies as they operate in various industries making them representative samples of industry analysis. Additionally, since publicly traded corporations are compelled by law to declare their financials, their financial information is more easily accessible than that of private enterprises. The study opted not to include financial companies because several studies have been performed on the application of technology in financial companies in Kenya which demonstrated that financial companies such as banks and insurance companies are highly automated.

Kemunto and Kagiri (2018), performed a study on Kenya Commercial Bank branches and found that process automation is the aspect that affects commercial banks' competitiveness the most, with mobile banking coming in second. The study suggested that banks should bolster their fintech plans to increase their competitiveness. Muigai and Gitau (2018) conducted a study with a specific focus on organizational innovation and product innovation and how they affect financial performance in Kenya's banking sector. The study's findings showed that organizational innovation and product innovation strategies have a positive and significant impact on the financial performance of Kenyan banking industry firms. Chepkwony (2018) performed a study on insurance companies in Nairobi County which determined that there was a substantial correlation between e-business strategies and insurance businesses' success and advised that insurance companies invest in IT infrastructure and create technology-enabled procedures. Tut (2023) investigated the effects of the coronavirus disease 2019 (COVID-19) pandemic on the adoption of Financial Technology in Kenya and concluded that the pandemic accelerated the adoption and increased concentration of Financial Technology in Kenya, further Fu and Mishra (2020) conducted a study in 74 nations to examine how the COVID-19 pandemic affected the uptake of fintech and digital finance. The study's findings showed that the pandemic had increased the use of new technologies by 24–32%.

The study therefore opted to use the financial period ended 2022 because this period had incorporated digital interventions that were done to enable companies to operate during the pandemic. According to the Capital Markets Authority Quarterly Statistical Bulletin issue 53/2022 for the quarter that ended December 2022, there were 63 listed companies in the NSE, and 34 were identified as non-financial companies, excluding suspended companies. This study involved obtaining primary data on emerging technologies applied in the finance function of listed non-financial companies and therefore the scope of the respondents will be limited to the Finance Directors or Chief Financial Officers or their delegates. Emerging technologies were limited to AI, Blockchain, Machine Learning, and RPA. Furthermore, the scope of the research was limited to semi-structured questionnaires.

1.6. Significance of the Study

The motivations behind the research as well as its advantages for different stakeholders are described in this section.

1.6.1. Companies

Kaya, et al. (2019), noted that emerging technologies have resulted in cost reduction, increased productivity, and enhanced decision-making through advanced analytics through the adaption of emerging technologies such as RPA. Since the main objective of the key management of listed entities is to maximize shareholder wealth, the results of the study will assist them understand how they can adopt emerging technologies that will enable them to maximize shareholder wealth.

1.6.2. Accounting and Finance Professionals and Academics

Zhang, et al. (2020), noted that the introduction of emerging technologies in the finance function had introduced significant changes to the accounting profession through the reengineering of accounting processes where manual and repetitive tasks were eliminated and finance professionals redeployed to more strategic finance roles. The study is therefore critically guiding finance professionals to understand the new role of finance professionals to remain competitive and for academicians to understand how the accounting curriculums need to change to ensure that the current accounting finance students are well equipped for future finance and accounting roles.

1.6.3. Regulators

As the finance function transforms, Regulators such as the Revenue Authorities and Capital Market regulators have been made aware of the opportunities and challenges that will arise from the adoption of these emerging technologies on their current scope of regulation and therefore enable them take advantage of the changes to optimize their operations.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

Chapter Two provides scholarly works that have been done about the adoption of emerging technologies. The chapter begins with the theoretical framework that supports the study and empirical studies on the application of emerging technologies in the finance function as well as organization characteristics that influence the adoption of emerging technologies. The chapter also presents a summary of knowledge gaps arising from this review which informs the conceptual framework and how the study variables have been operationalized at the end of the chapter.

2.2. Theoretical Review

The theoretical principles that relate to the application of emerging technologies in the finance function of listed non-financial firms in the NSE include The Diffusion of Innovation Theory (DOI) and Technology Organization Environment (TOE) framework. These theories are discussed in the section below.

2.2.1. Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation Theory (DOI) dates back in 1962, (Rodgers, 1962) and describes explains how new technology spreads through a population. DOI examines various approaches that are used to introduce new technologies into a social system (Almaiah et al.,2022). 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 explaining the theory, Rogers (2003) defines "diffusion as the process by which an innovation is gradually spread among the participants in a social system through certain channels". He went on to define adoption "as the choice to fully use an innovation as the best available course of action". The innovation-decision process, adaptor characteristics, and innovation characteristics are the three main components that the DOI model integrates. The characteristics of the innovation involve five key constructs which 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.

Five categories of adopter characteristics have been identified. These are innovators, who are the first to innovate and 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 of change and are most difficult group to bring on board, the late majority who 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. Five steps for the innovation-decision process have been identified and these include awareness, interest, evaluation, trial, and adoption. In summary, DOI evaluates characteristics of an organization, the attributes, and the environmental aspects in assessing the adoption of emerging technologies.

2.2.2. Technology Organization Environment (TOE)

The Technology Organization Environment (TOE) framework was developed by Lupi Tornatzky and Karen Klein in 1990 to study the technological adoption of various Information Systems (IS) and Information Technology (IT) services and products at the organizational level. According to Dube et al. (2020), TOE has emerged as a comprehensive theoretical perspective on IT adoption because it is not reliant on business size constraints, providing a full picture of the user's adoption of the technology, its implementation, anticipated challenges, impact on value chain operations, dissemination among companies post-adoption, factors influencing business innovation adoption decisions, and the development of improved organizational capabilities through the use of the technology. The TOE framework provides a systematic way of analyzing the factors that influence the adoption and diffusion of emerging technologies in organizations, including factors related to the technology itself, the organization, and the external environment. The framework is widely used in the field of information systems research and has been applied in numerous studies to understand the adoption and diffusion of various IS and IT services and products.

According to Seshadrinathan and Chandra (2021), the TOE provides a theoretical basis for doing empirical research on aspects that explain how the company context affects innovation adoption. The influencing factors are categorized into three groups: organizational, technological, and environmental.. Seshadrinathan and Chandra (2021) further comment that the technological context refers to equipment, processes, or practice related to the organization which may already be in use at the firm or available in the marketplace though not currently in use whilst the organizational context is related to the resources and the characteristics of the firm such as the size of the firm and managerial structure and the environmental context refer to the arena in which a firm conducts its business and is related to the surrounding elements such as industry, government policies, and competitors. Bryan and Zuva (2021) conclude that the TOE framework is used widely for theoretical perspectives on IT adoption because the technological, organizational, and environmental variables have made the framework invaluable over other selection models in contemplating innovation appropriation, innovation use, and creation of worth from innovation development.

This study applied both the DOI and TOE theories. The researcher applied the component of organization characteristics in the TOE theory and adopter characteristics in the DOI theory to achieve the first and second objectives of identifying the level of usage of emerging technologies in the finance function and identifying the features of listed companies in the NSE that have adopted these technologies. Company characteristics were grouped into three categories of company financial metrics, other company features, and finance department features which were used as independent variables for the characteristics of the company according to TOE theory or as the adaptor characteristics according to the DOI theory with the adaption of emerging technologies being the dependent variable. These independent variables provided useful insights into the level of complexity involved in the diffusion and adoption of innovations in the finance department.

2.3. Empirical Review

A preview of empirical reviews of previous studies on the adoption of emerging technologies and their application in the finance function is examined in the section 2.3.1, 2.3.2 and 2.3.3.

2.3.1. Empirical Reviews on the adaption of emerging technologies and their application in the finance function

In recent years, technological changes have resulted in disruptive technologies that continue to radically transform the finance and accounting profession through the automation of finance processes. Several studies have been performed on the impact of these emerging disruptive technologies and how companies can adopt these technologies. Zhang et al. (2020) performed a study on the Big Five accounting firms namely, PWC, PKF, KPMG, Deloitte, Ernst and Young, to examine the ways that blockchain, AI, machine learning, and RPA are being used in, highlighting the benefits and limitations of these new technologies as they are being used now. The study revealed that the accounting profession is increasingly investing in emerging technologies and integrating them into core business by applying technologies such as RPA to collect data, review financial statements and convert data into tax bases. Using blockchain and cloud technologies, AI was utilized to obtain large volumes of data and information for quick and accurate analysis. It was also used to download information on business rivals in the private chain and use that information directly to validate the data during the reconciliation process.. The study recommends that accounting professionals expand their technical knowledge to create more efficient accounting practices.

Kaya et al. (2019) undertook a study to establish the impact of RPA technologies on accounting systems. The study was aimed at identifying the implementation and improvement areas of RPA in financial reporting systems as well as the effects of RPA technologies on traditional accounting and cost accounting processes. The study concluded that RPA will result in the automation of routine, standardized, manually operated, and time-consuming tasks in virtually all spheres of accounting such as data entry and electronic verification and certification of supporting documentation in the accounts payable and accounts receivable processes, general accounting tasks such as cost allocation, journal entries, and account reconciliations, budgeting and forecasting functions such as scenario planning and automation of control activities which will result in focusing of the finance function on strategic and analytical tasks that support core business objectives. The study recommended that some future studies be performed to research the implementation of RPA in companies successful case studies of the use of RPA be highlighted. Additionally, Li et al. (2020) revealed that AI liberates finance and accounting professionals from low-level repetitive work thereby changing their focus to providing business leaders with information to support business decisions. The study concluded that the expertise of accounting and finance professionals is changing into demanding a complex multi-disciplinary skill set and recommended that an investigation into new risks and challenges brought about by AI such as accounting information security and over-reliance on technology be performed.

Lacity et al. (2015) performed a case study on Robotic process automation at Telefonica O2, a telecommunications services provider. The Company was one of the early adopters of RPA and the study highlighted that as of April 2015, the Company had automated over 35 percent of its transactions in 15 core processes which included SIM swaps, credit checks, order processing, customer reassignment, and customer data updates, resulting in radically transforming the back offices to deliver lower cost whilst improving service quality, increasing compliance, and decreasing delivery time. Some of the lessons learned in the automation journey in Telefonica included that RPA needs to be combined with other tools such as process elimination and improvement, that robots need more explicit instructions than humans who can make some judgments based on common sense, and that the internal infrastructure needs to grow at the same pace with automation.

Bisht et al. (2022) carried out a study on the adoption of emerging technologies, such as big data and AI technology for the possibility of an automated personal assistant that can analyze financial markets and make smart financial decisions, IoT and blockchain with smart contracts to secure financial documents and risk, and the Internet of Things (IoT), cloud computing, big data, RPA, AI, Blockchain, digital twin, and Metaverse in the financial management of a firm was recommended in a study discussing the role of emerging technologies in the financial management of a firm.. Emerson et al. (2020) performed a study aimed at identifying the applications of machine learning in the investment process and found out that a variety of Machine Learning techniques have been applied in solving portfolio optimization challenges resulting in the machine learning techniques outperforming traditional techniques. Additionally, return forecasts made from traditional inputs such as fundamental data or technical indicators were improved as well as improving traditional measures of risk used in the mean-variance framework. Zemánková (2019) performed a study aimed at providing an analysis of audit tasks that have benefitted from the implementation of AI and at providing an analysis of the implications of blockchain on auditing. The study identified seven audit tasks that have benefited from the implementation of AI, namely, evaluation of internal controls, risk assessment, analytical review procedures, balance classification, materiality assessments, going concern decisions, and bankruptcy prediction. Additionaly, the study identified that blockchain has changed the audit sampling methodology from selecting samples for testing-to-testing complete data sets due to data analytics capabilities, furthermore, the process of audit confirmation of outstanding receivables and payables would be eliminated in the future due to blockchain technology, providing real-time verification of all transactions. In contrast to repetitive, time-consuming, rules-based tasks, the study found that AI has the potential to greatly increase efficiency, decrease errors, and free up auditors' and accountants' time for more complex work. Blockchain, on the other hand, would help develop a new auditing methodology based on continuous assurance, which would necessitate an overhaul of the current professional audit standards.

Osman (2019) analyzed case studies on RPA implementation from different industries and functions such as telecommunications, insurance, finance, banking, the public sector, manufacturing, and public administration, and concluded that companies need to monitor their business processes continuously to identify and improve processes suitable for RPA such as those with a high volume of tasks, rule-based tasks or tasks with low-complexity in addition to standardized and mature processes as opposed to new processes. The study also proposed several best-in-class practices for a successful implementation of RPA which include the selection of suitable processes, standardization of the selected processes, ranking of activities in the processes based on their importance, the foundation of a team to organize and monitor RPA implementation and continuous monitoring of automated processes.

2.3.2. Empirical Reviews on the influence of organization characteristics on the adaption of emerging technologies

According to Asiaei and Rahim (2019), the resources available to support the adoption of a new technology are referred to as the organizational context. This addresses enterprise features like power and control distribution, degree of centralization, availability of spare resources, support from senior management, organizational size, and horizontal communication that either supports or impairs the implementation and adoption of an innovation. According to Salah et al. (2021), organizational features are factors that affect an innovation's decision to be adopted. Ilin et al. (2021), described organizational characteristics as unique features of an organization such as scope, size, and managerial structure, which may accelerate the adoption of emerging 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 emerging technologies providing conclusions about the influence of specific factors on the implementation of emerging technologies in companies. This section provides an analysis of the various organizational factors that have been previously studied. Ilin et al. (2021) performed a study aimed at identifying the factors that affect the adoption of e-business in enterprise resource planning (ERP) enabled firms using a research model based on DOI and TOE theories 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 e-business in ERP contrary to the commonly held belief that larger firms have more resources for committing required investments. 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 TOE 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 organisation size was significantly and positively related to the adoption and use of cloud technology. Khadrouf et al. (2021) performed a study to analyse how the characteristics of SMEs can determine the success or failure of

ERP implementation by using multiple case studies of SMEs in different sectors. The study concluded that ownership type and financial resources were the most influential contextual factors in the success or failure of ERP implementation. Bosman et al. (2020) investigated the role of firm size, access to funds, and industry type in deciding to invest and deploy emerging 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. Khlifi (2022) studied the relationship between Internet Financial Reporting (IFR) levels and corporate characteristics by testing a data set of 152 Tunisian companies. The results of the study showed that the variables that should be used to explain the level of IFR are firm size, ownership concentration, firm performance, and liquidity. 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. Hiebl et al. (2017) investigated the relationship between chief financial officer (CFO) traits and the adoption of enterprise resource planning (ERP) systems based on a survey of 296 large and medium-sized Austrian companies. The association between ERP system adoption and CFO traits was tested using a logistic regression analysis. The research found that firms with externally recruited CFOs have adopted ERP systems significantly more often than firms with internally promoted CFOs; firms with less educated CFOs frequently adopted an ERP system; and the relationship between CFO characteristics and ERP system adoption is not moderated by the CFO's responsibility for IT. The study used the CFO ages, employment, education, and staffing as independent variables. Faghani and Gyapong (2019) performed a study on the influence of firm characteristics and shareholder sophistication on the implementation of new legislation. The study found that board independence as measured by the number of non-executive directors divided by the total number of directors on the board at the year-end positively influenced the implementation of new legislation. 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 integrated reporting in mining companies 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. The study concluded that the board of commissioners, the board of independent commissioners, the audit committee, meeting attendance, company age, and size as control variables jointly influenced integrated reporting implementation. Pavlatos and Kostakis (2018) performed a study to explore the influence of the characteristics of the top management team and historical financial performance on strategic management accounting by studying 94 manufacturing companies operating in Greece. Historical financial performance was measured through return on investment, return on sales, return on equity, and earnings per share whilst top management characteristics of the Chief Finance Officer, Chief Executive Officer, and Chief Marketing Officers were measured by the educational background, tenure, and creativity. The study found that companies that had historically low profitability adopted and used innovative SMA tools more extensively to improve their financial performance in the future and that top management characteristics of educational background, tenure, and creativity affected the adoption and usage of strategic management accounting tools. Ginesti et al. (2021) studied a sample of the largest European listed companies for the period 2013–2016 to test the association between CFO education, CFO gender, and CFO age with R&D investment intensity. According to the study's findings, the intensity of R&D expenditure was positively correlated with the presence of female CFOs, CFOs with a Master of Business Administration (MBA) or Doctor of Philosophy (Ph.D.) degree, and older CFOs.

2.3.3. Empirical Reviews on the challenges and opportunities in the adaption of emerging technologies

Udo et al. (2024) performed a comparative analysis of Africa and the United States of America to identify the trends and challenges of adopting emerging technologies and identified four challenges which include inadequate ICT infrastructure and limited accessibility of internet access, fragmented and outdated policy and regulatory environment, socio-economic disparities such as education and lack of the required skills and cultural and ethical considerations which include privacy concerns that may deter companies from adopting the emerging technologies. The study recommended the introduction of innovative solutions to address the challenges in Africa, cross-continental collaborations, and the prioritization of investment in ICT infrastructure in Africa.

Benbya et al. (2020), who performed a study on AI in organizations aimed at identifying the current state and future opportunities, noted that AI in most organizations is experimental and rarely deployed into production due to challenges such as integration of AI with existing technology architectures and legacy infrastructure, implementation of required changes in business processes and organizational culture, reskilling or upskilling of employees, substantial data engineering, and approaches to organizational change management. The study recommended that companies begin working on developing AI applications that create economic and upskill workers to do existing jobs with AI and retrain and hire others for the new roles that AI will demand.

According to Gotthardt et al. (2020), cybersecurity and the vulnerability of emerging technologies to attacks from malicious users is a key challenge, however, countermeasures are readily available and under continuous development, further, the researcher noted that sufficient resources are required for implementation of emerging technologies.

Drawing from various research, it's evident that while emerging technologies hold immense potential to revolutionize financial processes, several obstacles impede their widespread implementation. While studies conducted in other regions provide valuable insights, the applicability of their findings to Kenya may vary due to unique contextual factors. Therefore, conducting this research tailored to Kenya's circumstances would provide targeted recommendations and solutions that account for the country's specific needs and challenges. This localized approach is crucial for informing policymakers, businesses, and other stakeholders in Kenya on how to effectively navigate the adoption of emerging technologies in finance functions and maximize their benefits while mitigating potential risks.

2.4. Research Gap

Empirical results have focused on identifying the finance and accounting processes in which the emerging technologies can be applied, the immense benefits that will be derived from implementing the emerging technologies, and how these emerging technologies will impact the accounting profession in the future. The results of these studies are aligned in that most of the finance and accounting processes ranging from manual, standardized, and repetitive tasks to complex processes can be automated resulting in immense cost, productivity, and compliance benefits to firms and in the future, the skill set of accounting and finance professionals will change into a demanding and complex multi-disciplinary skill set incorporating both information technology and finance and accounting skills. Further, Lacity et al. (2015) performed a case study on the proof of concept of RPA in a telecommunications company whilst Zhang et al. (2020) demonstrated how the Big 4 accounting firms have applied the emerging technologies in their core operations. Additionally, Emerson et al. (2020) performed a study on the investment process in financial services companies. Based on the empirical studies reviewed, showed that a holistic study has not been performed to assess the extent to which the emerging technologies have been adopted by a broad range of companies in diverse sectors such as non-financial companies listed in the NSE, furthermore a similar study to assess the application of these emerging technologies in Kenyan companies in a bid to assess the extent to which Kenyan companies have adopted these technologies has not been performed. This study aimed to bridge this research gap.

2.5. Conceptual Framework

Conceptual framework refers to a diagrammatic presentation of the relationship among study variables. From the framework, the dependent variable was measured as a dichotomous variable where 1= adoption of emerging technologies in the finance function and 0= emerging finance technologies have not been adopted in the finance function. The literature review section identified company characteristics that have been used in previous studies and their impact on technology adoption. In this study, company characteristics were 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 focused on.

Figure 1: Conceptual Framework

Independent Variables

Company Financial Metrics

- Profitability
- Liquidity
- Company Size

Other Company features

- Board Independence
- Company age
- Ownership concentration

Finance Department Characteristics

- Number of Employees in the Finance Department
- Chief Finance Officer age
- Chief Finance Officer tenure

Dependent Variables

Adoption of Emerging Finance Technologies (Artificial Intelligence, Robotic Process Automation, Machine Learning, and Blockchain) (Dichotomous Variable where 1= emerging technologies have been adopted in the finance function and 0= emerging finance technologies have not been adopted in the finance function.

2.1. Operationalization and Measurement of Variables

The Operationalization of variables is presented in the table below:

Table 2.1 Operationalization of Variables

Variable	Level of measurement	Description & Measurement Indicator	Reference
Dependent			
Application of emerging Finance Technologies	Dichotomous	Indicates whether company has adapted emerging technologies (=1) or has not adapted emerging technologies (=0)	Hiebl et al. (2017)
Independent			
Company Profitability (OM)	Metric	Operating margin is measured as the percentage of operating income divided by the revenue during a period.	Pavlatos and Kostakis (2018)
Company Liquidity (QR)	Metric	Quick ratio measured as current assets divided by Current liabilities	Khlifi (2022)
Company Size (TA)	Metric	Natural logarithm of total assets at the end of the fiscal year	Bosman et al. (2020)
Board Independence (BI)	Metric	The number of non-executive directors divided by the total number of directors in the board at year-end	Faghani and Gyapong (2019)
Company age (CA)	Metric	Natural logarithm of the duration in years that the company has been listed in the NSE	Yulyan et al. (2017)

Variable	Level of measurement	Description & Measurement Indicator	Reference
Ownership concentration (OC)	Metric	The percentage of company shares owned by the top 5 shareholders at year-end.	Khadrouf et al. (2021)
Number of employees in Finance function (EF)	Metric	Natural logarithm of the number of employees in the Finance function.	Ilin et al. (2021)
CFO age (CFA)	Dichotomous	Indicates whether the CFO's age is over 45 years (=1) or equal to or lower than 45 years (=0)	Ginesti et al. (2021)
CFO tenure (CFT)	Metric	Tenure of the CFO in the current position in years	Hiebl et al. (2017)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. Introduction

The chapter presents the methodology adopted in achieving the research objectives outlined and discussed in chapter 1. This chapter covers the research philosophy, research design, population and sampling, data collection methods and tools, data analysis, quality of the research, and ethical considerations.

3.2. Research Philosophy

The study adopted a positivist approach to research. The aim of positivist studies is to consistently be rational and use logical approaches to seek objectivity (Saunders, Lewis, & Thornhill, 2012). In positivist paradigm, the researcher gathers and analyzes information objectively, employing statistical and mathematical techniques to draw conclusions. Research data and findings are typically measurable and observable. Furthermore, the positivist approach requires that researchers be objective about the topic, (Saunders et al., 2012). However, the authors also explain that it may be impossible to completely remain objective. This is because the researcher still has decisions to make regarding what to examine, how to put together objectives, and what data to gather. The study's use of semi-structured questionnaires to refine the results and secondary data to ascertain the link between variables made the positivist method appropriate.

3.3. Research Design

According to Saunders et al (2019), the research design is the general plan of how you will go about answering your research questions and should contain clear objectives derived from research questions, a specification of the data source, a proposal on how the data will be collected and analyzed and a discussion of ethical issues and the constraints that you may encounter. Kothari (2004) noted that a research design facilitates the smooth flow of various research operations to yield maximum information with minimal cost, time, and effort. Research designs can be categorized into four broad groups, which include exploratory research studies, descriptive research studies, explanatory research studies, and evaluative research studies. Saunders et al (2019), explained that the emphasis of descriptive research is to gain an accurate profile of events, persons or situations, therefore this study selected a descriptive research design. This approach was selected because it was found to be appropriate to gain an accurate profile of the adoption of emerging finance technologies by listed non-financial companies. The study used quantitative data collected from both secondary and primary data sources to gain an accurate profile on the adoption of emerging finance technologies in the finance function and the effect of specific company characteristics on the adoption of emerging finance technologies by listed non-financial companies, furthermore, the study used qualitative data that was collected through a questionnaire to provide rich insights into the motivations, barriers, and facilitators of adoption of emerging technologies.

3.4. Population and sampling

3.4.1. Target Population

According to Cooper and Schindler (2014), while a sample evaluates a subset of the study population, and that it must be carefully chosen to represent the population as a whole, the target population is defined all the individuals that must be analysed. As referenced in section 1.5, this study opted not to include financial companies because several studies have been performed on the application of technology in financial companies in Kenya which have concluded that financial companies such as banks and insurance companies are highly automated. According to the Capital Markets Authority Quarterly Statistical Bulletin issue 53/2022 there were 63 listed companies in the NSE. The listed companies are classified into 13 segments, out of which 7 segments, namely, agricultural, automobiles and accessories, commercial and allied services, construction and allied, energy and petroleum, manufacturing and allied, and telecommunication fit into the definition of non-financial companies as defined by the Organization for Economic Cooperation and Development (OECD) which defines non-financial companies as "companies whose principal activity is the production of market goods or non-financial services".

3.4.2. Sampling Technique

The study adopted census sampling technique since the population was well-defined and small, for more accurate and reliable data. The 7 non-financial segments had a total of 38 companies, however, 4 of these companies had been suspended from trading in the NSE under the period of study. The study therefore focused on the entire population comprising of the 34 companies (Refer to Appendix III for a complete list). To obtain relevant information to solve the research problem, the research study targeted the Finance Directors or equivalent roles in the 34 companies in the population. The study, therefore, targeted to receive 34 completed questionnaires from the respondents.

3.5. Data Collection Method and Tools

Research data was collected from both primary and secondary data sources. Data on company financial metrics, board independence, ownership concentration, and company age were collected from secondary data sources in the annual audited financial statements for the financial period ended in 2022 that are published and submitted to Capital Markets Authority. Data on number of employees in the finance function, the CFO age and CFO tenure, and other qualitative data was collected from primary data sources through self-administered questionnaires over a duration of one month. All the questionnaires were administered in person to respondents accompanied by an introductory letter introducing the researcher and the objective of the study (Refer to Appendix I for the introductory letter and Appendix II for the Questionnaire). The questionnaires were administered to Finance Directors or equivalent roles in the 34 companies in the population.

The development of the research questionnaire was steered by the conceptualization of the research variables and supported by prior empirical literature in the subject area and used a mix of closed-ended, open-ended as well as list questions that offered the respondent a list of responses from which one or more responses were to be chosen. The questionnaire was designed consistent with the objectives of the study, the first section contained questions about the company profile and respondent opinions. The second section addressed the structure of the finance department and the level of automation of finance processes, while the third section had questions regarding the adaptation of emerging technologies. Some of the responses were assessed using a five-point Likert scale that described the extent to which the statements described the firms under study with values ranging from *1= neither agree nor disagree – 5 = strongly agree.*

3.6. Data Analysis

The analysis intended to establish the influence of company features on the adoption of emerging technologies by the finance functions of listed non-financial companies in the

NSE. The company characteristics were grouped into three dimensions of company financial metrics, namely company profitability, liquidity, and size, other company features, namely board independence, ownership concentration, and the duration for which the company has been listed in the NSE and finance department characteristics, namely the number of employees in the finance function, the CFO age and CFO tenure as the independent variables.

The dependent variable was the application of emerging technologies in the finance function which was a dichotomous variable whereby 1= application of emerging technologies in the finance function and 0= emerging finance technologies have not been applied in the finance function. According to (Gujarati, 2011), Linear Probability Models (LPM) are not the preferred choice for modelling dichotomous variables because LPM assumes that the probability of the independent variable moves linearly with the value of the explanatory variable, secondly it is not guaranteed the estimated probability values will lie between 0 and 1 and finally, if the dependent variable is between 0 and 1, then the assumption that the error term is normally distributed may not be neccessary. Therefore a binary logistic regression model was used for this study because a binary regression model is most appropriate when the dependent variable is dichotomous, and the independent variables are a combination of continuous and dichotomous variables. Analysis of this study was done based on the model below:

$$\text{Log}(P/1\text{-}P) = \alpha_i + ß_1 OM_{it} + ß_2 QR_{it} + ß_3 TA_{it} + ß_4 BI_{it} + ß_5 CA_{it} + ß_6 OC_{it} + ß_7 EF_{it} + ß_8 CFA_{it} + ß_9 CFT_{it} + U_{it}$$

The symbols represent the following variables

Table 3.1 Symbols Representing Variables

Symbol	**Meaning**
α_i	Constant
OM_{it}	Operating margin
$ß_1$	Operating margin coefficient
QR_{it}	Quick ratio

Symbol	Meaning
ß$_2$	Quick ratio coefficient
TA_{it}	Total assets
ß$_3$	Total assets coefficient
BI_{it}	Board independence
ß$_4$	Board independence coefficient
CA_{it}	Company age
ß$_5$	Company age coefficient
OC_{it}	Ownership concentration
ß$_6$	Ownership concentration coefficient
EF_{it}	Number of employees in the finance function coefficient
ß$_7$	Number of employees in the finance function
CFA_i	CFO age
ß$_8$	CFO age coefficient
CFT_{it}	CFO tenure
ß$_9$	CFO tenure coefficient
U_{it}	Error Term
P	P is the probability of the dependent variable taking on the value 1 (as opposed to 0) where 1 = Emerging technologies (AI, RPA, Blockchain, or Machine Learning) have been adapted and 0 = Emerging technologies have not been adapted

Some of the qualitative data responses were assessed using a five-point Likert scale that described the extent to which the statements described the companies under study and descriptive statistics used to interpret the data.

3.7. Research Quality

An important consideration in determining the value of a research is its quality. It is essential to consider the legitimacy and trustworthiness of the data acquired in order to guarantee the caliber of the research. The degree to which the research measures what it intends to measure is referred to as validity. (Creswell, 2014). On the other hand, reliability ensures the consistency of the results over time and with different researchers (Polit & Beck, 2012). To improve the validity and reliability of the results, a combination of qualitative and quantitative research methods was used in this study. Data from structured questionnaires was more uniform and broadly applicable. Additionally, the study's validity and reliability were improved by the triangulation of data from other sources. The researcher carried out a pre-test before actual data collection is done using the primary data collection instrument (questionnaire) to test for relevance, interpretation of questions, proper wording, and clarity of the questions. Data was then analyzed using the Cronbach's Alpha Coefficient method where a correlation coefficient of 0.8 is desirable for reliability. The Cronbach's Alpha (α) Coefficient was interpreted as below:

1. Complete internal consistency: $\alpha = 1$
2. No internal consistency: $\alpha = 0$
3. The closer it is to 1: the higher the reliability.

The results of Cronbach's alpha results are shown in table 3.2 below.

Table 3.2 Cronbach's Alpha

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of items
0.878	0.883	8

Source: (Research data,2023)

Since the Cronbach's alpha is above 0.8, the instrument was considered to be reliable for data analysis. The researcher ensured that the secondary data was obtained from authentic sources.

3.8. Ethical Considerations

Ethical guidelines were met and followed during the entire research process. High secrecy was maintained when gathering primary data from the respondents to guarantee that the results accurately reflected the data that was analyzed. The study adhered to anonymity in the dissemination of the data received from the respondents by making sure the material was utilized only for academic purposes. The respondents participated voluntarily, and their responses were kept confidential. The proposal will be submitted to the Strathmore Institutional Ethics and Scientific Review Committee (SERSRC) for ethical approval and will also be submitted to the local regulator, National Commission for Science, Technology, and innovation (NACOSTI) for approval. To avoid plagiarism all scholars whose work was used in the study were cited and referenced, additionally, permission was sought from Strathmore University to carry out the research study.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.1 Introduction

This chapter highlights the data analysis and presentation and has been organized into several sections. Chapter 4.2 presents the study response rate; section 4.3 summarizes the bio-demographic data; section 4.4 covers the descriptive data analysis for the study; Section 4.5 discusses the diagnostic tests performed and section 4.6 presents the inferential analysis of the data. Section 4.7 provides additional discussion on qualitative data obtained from the questionnaire and finally, section 4.8 provides an overall summary of the chapter.

4.2 Response rate

The study targeted 34 non-financial companies listed in the NSE and collected both secondary and primary data. The secondary data was collected from the annual reports of the companies whilst the primary data was collected through questionnaires distributed to the respondents, Finance Directors, or equivalent roles of the 34 companies. The study response rate was captured in Table 4.1 below which indicates a response rate of 68%. According to (Fincham,2008), a 60% response rate is the goal of most researchers, the response rate was therefore considered sufficient to enable the researcher to analyze the data collected.

Table 4.1 Response Rate

Response	Frequency	Percentage
Responded	23	68%
Did not Respond	11	32%
Total	**34**	**100%**

Source: (Research data,2023)

4.3 Demographic Data

The demographic data of the respondents who participated in the study was analyzed and the output was presented in this section. Demographic information is critical because it can influence the adoption and implementation of emerging technologies in the finance function. Table 4.2 below highlights the demographic data in relation to the gender, length of service in the organization of the Finance Director or CFO and the number of employees in the finance department.

Table 4.2 Demographic data response

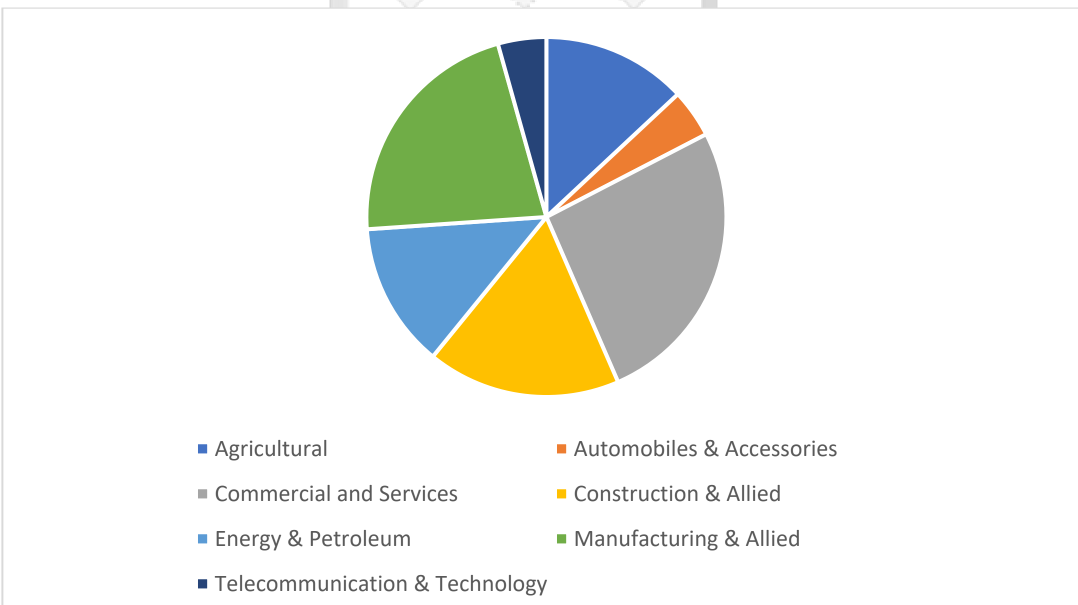
Variable	Frequency	Percentage
Gender		
Male	18	78.0%
Female	5	22.0%
Total	**23**	**100.0%**
Length of service in the organisation of the Finance Director/CFO (Years)		
Less than 3	12	52.0%
4-7	5	22.0%
8-11	2	9.0%
Over 12	4	17.0%
Total	**23**	**100.0%**
Number of employees in the Finance Department		
Less than 19	12	52.0%
20-39	1	4.0%
40-50	9	39.0%
Over 60	1	4.0%
Total	**23**	**100.0%**

Source: (Research data,2023)

From the results in Table 4.2 above, the majority of Finance Directors or equivalent roles in listed non-financial companies in the NSE are male (78.0%), while females constitute a smaller percentage (22.0%) which suggests a high disparity in occupancy of top finance leadership positions in listed non-financial companies in Kenya. More than half of the Finance Directors/CFOs have a length of service of less than 3 years (52.0%) which might indicate a recently appointed group of leaders in the finance department. A notable portion has a service length of 4-7 years (22.0%), and a smaller percentage have service lengths of 8-11 years (9.0%) and over 12 years (17.0%). This distribution reflects a range of experience levels within the finance leadership roles. The majority of Finance Departments have less than 19 employees (52.0%) whilst a substantial percentage (39.0%) have 40-50 employees demonstrating the diversity in the size of the finance departments of listed non-financial companies.

Figure 4.1 below presents the analysis of the respondents who completed the questionnaire according to their industries demonstrating that there were responses from all the industries of the listed non-financial companies furthermore, no single industry dominates the sample, indicating a balanced representation across different industries.

Figure 4.1 Respondents' Industry



Source: (Research data,2023)

4.4 Descriptive Results

This section presents the descriptive results of study variables as well as the primary data collected through questionnaires. Tabulation was conducted and presentation was done in the form of frequencies for categorical independent and dependent variables as well as the primary data collected from the questionnaire whilst the minimum, maximum, mean, and standard deviation were tabulated for the metric dependent variables. Further, the researcher tabulated the group statistics for the categorical dependent variable in two distinct groups of those Companies that had adopted emerging technologies and those that had not adopted emerging finance technologies.

4.4.1 Metric Independent variables

Table 4.3 below presents the descriptive statistics for the metric independent variables and highlights the mean of the independent metric variables, the standard deviation, maximum and minimum values.

Table 4.3 Descriptive statistics for metric independent variables

Metric Variable	N	Minimum	Maximum	Mean	Standard Deviation
Company Profitability	23	-85.85%	64.84%	10.31%	27.08%
Company Liquidity	23	0.1427	9.8242	2.1739	2.2935
Company Size	23	1,212,627	509,224,735	15,966,447	5,839,500
Board Independence	23	33.33%	100.00%	78.58%	16.82%
Company age	23	8.0	69.0	34.0	1.9022
Ownership concentration	23	55.60%	95.36%	79.69%	10.12%
Number of employees in Finance function	23	4.0	220	22	2.7154
CFO tenure	23	1.0	16.0	4.0	2.2190

Source: (Research data,2023)

The average company profitability as measured by operating margin is 10.31% and there is a wide standard deviation of 27.08% which demonstrates that there is a substantial variation in profitability among non-financial companies listed in the NSE as demonstrated by some companies reporting significant losses (minimum at -85.85%), while others report substantial gains (maximum at 64.84%). The average liquidity index is 2.1739, with a moderate standard deviation of 2.2935, further, the company liquidity ranges from 0.1427 to 9.8242 and demonstrates diverse liquidity levels across the non-financial companies listed in the NSE. The average size of the companies measured by the total assets at the end of the financial year is Shs 15,966,447, with a standard deviation of Shs 5,939,500, further, the size of the companies ranges from Shs 1,212,627 to Shs 509,224,735 indicating variability, however, the non-financial companies listed in the

NSE are moderately close in size. The average age of companies as measured by the duration in years that the company has been listed in the NSE is 34, with a relatively small standard deviation of 1.9022, further, the range from 8 years to 69 years indicates moderate diversity in the age of non-financial companies listed in the NSE. On average, the boards of companies listed in the NSE exhibit a high level of independence with an average of 78.58%, however, there is a notable variability as demonstrated by the standard deviation of 16.82%, in addition, the range from 33.33% to 100.00% suggests that there is diversity in the composition of boards of the listed non-financial companies. The average ownership concentration is 79.69%, with a standard deviation of 10.12% whilst the range from 55.60% to 95.36% shows variability, with some of the listed non-financial companies having concentrated ownership levels. The average number of employees as measured by the number of employees in the finance department is 22, with a standard deviation of 2.7154 with a range from 4 to 220 that indicates variability in the size of finance functions across listed non-financial companies. The average CFO tenure measured by the number of years served as CFO is 4, with a standard deviation of 2.219, and the range from 1 to 16 suggests significant variability in the tenure of CFO's of listed non-financial companies.

4.4.2 Categorical independent variable

Table 4.4 below presents the descriptive statistics of the categorical independent variable, CFO Age, in form of frequency.

Table 4.4 CFO Age

CFO Age	Frequency	Percentage
Equal to or below 45 years	9	39.1%
Over 45 years	14	60.9%
Total	**23**	**100.0%**

Source: (Research data,2023)

A substantial proportion of CFOs (60.9%) are over 45 years which suggests that the majority of the non-financial companies listed in the NSE prefer experienced CFOs who can contribute seasoned leadership and strategic experience.

4.4.3 Categorical Dependent Variable

Univariate and group descriptive statistics were performed for the categorical dependent variable, and these are presented in section 4.4.3.1 and 4.4.3.2 respectively.

4.4.3.1 Univariate Descriptive Statistics for the Categorical Dependent Variable

Table 4.5 below presents the univariate descriptive statistics of the categorical dependent variable, Application of emerging Finance Technologies, in form of frequency.

Table 4.5 Application of emerging finance technologies

Application of emerging finance technologies	Frequency	Percentage
Has adapted emerging finance technologies	5	21.7%
Has not adapted emerging finance technologies	18	78.3%
Total	**23**	**100.0%**

Source: (Research data,2023)

A significant majority of 78.3% of non-financial listed companies have not adopted emerging finance technologies which implies a slow pace in incorporating emerging financial technologies into finance operations. Table 4.6 below further presents an analysis of the types of technologies that have been adopted by non-financial companies listed in the NSE.

Table 4.6 Types of technologies adopted.

Type of technology	Frequency	Percentage
Robotic Process Automation ("RPA")		
Not Adopted	19	82.6%
Adopted	4	17.4%
Total	**23**	**100.0%**
Machine Learning		
Not Adopted	21	91.3%
Adopted	2	8.7%
Total	**23**	**100.0%**

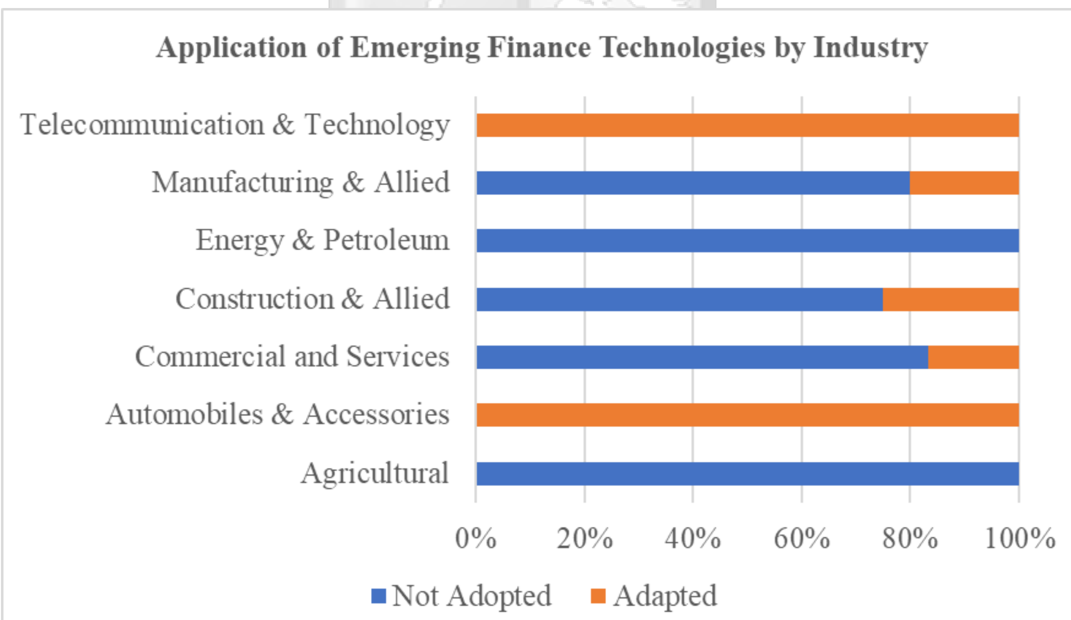
Type of technology	Frequency	Percentage
Blockchain		
Not Adopted	23	100.0%
Adopted	0	0.0%
Total	**23**	**100.0%**
Artificial Intelligence (AI)		
Not Adopted	21	91.3%
Adopted	2	8.7%
Total	**23**	**100.0%**

Source: (Research data,2023)

There is a prevailing trend of non-adoption of emerging technologies in the finance department of non-financial companies listed in the NSE. RPA has a comparatively higher adoption rate than other technologies, while Blockchain has zero adoption.

Figure 4.2 below presents an analysis of adoption of emerging finance technologies according to the industry classification in the NSE.

Figure 4. 2 Application of emerging finance technologies by industry classification



Source: (Research data,2023)

Figure 4.2 above presents data on the application of emerging finance technologies across the industries as classified by the NSE. None of the companies in the Agricultural and Energy and Petroleum industries had adopted the emerging finance technologies, in contrast, all the companies in the Telecommunication & Technology and Automobiles & Accessories industries, had adopted the emerging finance technologies whilst the Commercial and Services and Manufacturing and Allied industries showing significantly high rates of non-adoption.

4.4.3.2 Group Descriptive Statistics for the Categorical Dependent Variable

Table 4.7 below presents group descriptive statistics of the categorical dependent variable, Application of emerging Finance Technologies, in form of mean, standard deviation and standard error mean.

Table 4.7 Application of emerging finance technologies by industry classification

Independent variable	Application of emerging Finance Technologies	N	Mean	Standard Deviation	Standard Error Mean
Company Profitability	yes	5	0.1300	0.1342	0.0600
	No	18	0.0408	0.3938	0.0928
Company Liquidity	yes	5	1.7116	1.1160	0.4991
	No	18	2.3023	2.5366	0.5979
Company Size	yes	5	17.9405	1.4964	0.6692
	No	18	16.2097	1.6770	0.3953
Board Independence	yes	5	0.8400	0.0682	0.0305
	No	18	0.7711	0.1866	0.0440
Company age	yes	5	3.4779	0.7792	0.3485
	No	18	3.5287	0.6262	0.1476
Ownership concentration	yes	5	0.7480	0.0554	0.0248
	No	18	0.8111	0.1082	0.0255
Number of employees in Finance function	yes	5	3.6792	1.2012	0.5372
	No	18	2.9417	0.9097	0.2144

Independent variable	Application of emerging Finance Technologies	N	Mean	Standard Deviation	Standard Error Mean
CFO age	yes	5	0.8000	0.4472	0.2000
	No	18	0.5556	0.5113	0.1205
CFO tenure	yes	5	0.9810	0.5913	0.2645
	No	18	1.5975	0.8082	0.1905

Source: (Research data,2023)

From the results in table 4.7 above, the findings indicate that companies that have adopted the emerging finance technologies have a higher means for company profitability, company size, board independence and employees in the finance department, whilst they have lower means for the company liquidity, ownership concentration and CFO tenure, there was a marginal difference in the mean of the CFO age.

4.4.3.3 Mann-Whitney U Test for Group Descriptive Statistics for the Categorical Dependent Variable

According to Allahverdi, et al. (2017), The Mann-Whitney U test is a non-parametric test that is used for the analysis of the differences between two independent groups. This test was therefore used to assess whether there exists a significant difference between the two independent groups of non-financial companies listed in the NSE that adopted the emerging finance technologies and those who have not adopted the emerging finance technologies for the nine independent variables. The SPSS statistical program was used for the analysis of the data and the results of the analysis are tabulated in Table 4.8 below.

Table 4.8 Mann-Whitney U Test Results.

Test Statistics[a]					
Independent variable	**Mann-Whitney U**	**Wilcoxon W**	**Z**	**Asymp. Sig. (2-tailed)**	**Exact Sig. [2*(1-tailed Sig.)]**
Company Profitability	66.000	472.000	-0.201	0.841	.865[b]
Company Liquidity	69.000	84.000	-0.050	0.960	.981[b]
Company Size	20.000	426.000	-2.510	0.012	.009[b]
Board Independence	50.500	456.500	-0.981	0.327	.338[b]
Company age	67.000	473.000	-0.151	0.880	.903[b]
Ownership concentration	45.000	60.000	-1.255	0.209	.226[b]
Number of employees in Finance function	21.000	427.000	-2.460	0.014	.011[b]
CFO age	51.500	457.500	-1.085	0.278	.364[b]
CFO tenure	36.000	51.000	-1.732	0.083	.093[b]
a. Grouping Variable: Application of emerging Finance Technologies					
b. Not corrected for ties.					

Source: (Research data,2023)

The results revealed that there was a statistically significant difference in company size and the number of employees in the finance function between companies that adopted emerging finance technologies and those that did not as the p-value was less than the significance level of 0.05. Conversely, no significant differences were observed in profitability, liquidity, board independence, company age, ownership concentration, CFO age, and CFO tenure.

4.5 Diagnostic Tests

The section outlines the prior tests that were conducted for the binary logistic regression model. The study performed diagnostic tests before commencing on the binary logistic regression model and these are described in section 4.5.1 and section 4.5.2.

4.5.1 Test for Normality

The test for normality was performed using the Shapiro-Wilk test using the SPSS software. Shapiro-Wilk test is used to test the null hypothesis that a sample comes from a normally distributed population, where the p-value should be greater than 0.05 ($p>0.05$).

This test establishes the extent of normality of the data by detecting the existence of skewness or kurtosis or both. Data is normally distributed when the test results are statistically insignificant. Shapiro-Wilk statistic ranges from zero to one with figures higher than 0.05 indicating that the data is normal (Razali & Wah, 2011). Table 4.9 below tabulates the test results for the Shapiro-Wilk test.

Table 4.9 Shapiro-Wilk Normality Test.

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
Independent variable	**Statistic**	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Company Profitability	0.324	23	0.000	0.757	23	0.000
Company Liquidity	0.241	23	0.001	0.756	23	0.000
Company Size	0.144	23	.200*	0.931	23	0.112
Board Independence	0.152	23	0.178	0.867	23	0.006
Company age	0.295	23	0.000	0.851	23	0.003
Ownership concentration	0.133	23	.200*	0.958	23	0.425
Number of employees in Finance function	0.183	23	0.045	0.927	23	0.093
CFO age	0.198	23	0.020	0.895	23	0.020
CFO tenure	0.392	23	0.000	0.622	23	0.000
*. This is a lower bound of the true significance.						
a. Lilliefors Significance Correction						

Source: (Research data,2023)

The results tabulated in Table 4.9 show that the Company Profitability, Liquidity, Age, and CFO Age exhibited deviations from normality, as indicated by both the Kolmogorov-Smirnov and Shapiro-Wilk tests ($p < 0.05$). Conversely, variables such as Company Size and Ownership Concentration showed discrepancies in their assessments, with the Kolmogorov-Smirnov test suggesting normality while the Shapiro-Wilk test indicated departures. From the normality test described in the subsection above, the data did not meet the assumption of a parametric test. Therefore, the study employed the Mann-Whitney U-test, a non-parametric test, to assess the differences in perceptions between companies listed on the NSE that adopted emerging finance technologies and those that have not. The findings are presented in Table 4.8. under subsection 4.4.3.3. The test results guided subsequent statistical analyses, ensuring the selection of appropriate methods that account for the observed distributional characteristics.

4.5.2 Test of multi-collinearity

A multi-collinearity test was conducted to assess whether a high correlation existed between study variables. Multi-collinearity occurs when some independent variables are correlated with one another, when this association is high, the prediction abilities of each predictor variable is affected (Mugenda & Mugenda, 2003). The multi-collinearity test was computed using the Variance Inflation Factors (VIF). According to Kock (2015) when the VIF is around or greater than 10 there is a high degree of multicollinearity while a VIF less than 10 shows little to no existence of multicollinearity among the variables. Table 4.10 below tabulates the test results for the VIF test.

Table 4.10 Test of Multi-collinearity

Independent variable	**VIF**	**1/VIF**
Company Size	2.83	0.353161
Number of employees in Finance function	2.47	0.405025
Board Independence	1.97	0.508782
CFO age	1.94	0.514978
Ownership concentration	1.88	0.530748
Company Liquidity	1.68	0.595472
Company Profitability	1.66	0.604189
Company age	1.22	0.822131
CFO tenure	1.15	0.872137
Mean VIF	**1.87**	

Source: (Research data,2023)

The evaluation of Variance Inflation Factors (VIF) for the independent variables in our regression analysis reveals that the VIF values consistently remain below the commonly accepted threshold of 10 indicating a low level of multicollinearity and demonstrating that the independent variables are relatively independent of each other within the regression model. The mean VIF of 1.87 further reinforces the absence of significant multicollinearity concerns, supporting the robustness of our regression model and the reliability of parameter estimates.

4.6 Inferential Statistics

The chapter presents the inferential analysis that was performed to establish the nature and magnitude of the relationships between study variables. The section is divided into four sections that covered the Correlation coefficients matrix test in Section 4.6.1, the Binary Logistic Regression Model in section 4.6.2, Goodness of fit tests in Section 4.6.3 and an analysis of the Binary Logistic Model in Section 4.6.4.

4.6.1 Correlation Coefficients Matrix Test

Spearman's rho, a non-parametric statistical measure, was employed to assess the strength and direction of monotonic relationships between study variables. Spearman's rho was preferred because it does not assume a linear relationship and is particularly suitable for variables with ordinal or ranked data. Spearman's rho ranges from -1 to 1, where a value of 1 indicates a perfect positive monotonic relationship, -1 signifies a perfect negative monotonic relationship, and 0 denotes no monotonic relationship. The significance of Spearman's rho was determined through hypothesis testing, involving a two-tailed test with the null hypothesis assuming no correlation. The associated p-value was compared to the predetermined significance level of 0.05, to ascertain whether the observed correlation was statistically significant. Table 4.11 below tabulates the test results for Spearman's rho test.

Table 4.11 Spearman's rho Correlation Coefficients Matrix test table

		y	**OM**	**QR**	**TA**	**BI**	**CA**	**OC**	**EF**	**CFA**	**CFT**
y	Correlation Coefficient	1.000	-0.064	0.032	.461*	0.088	-0.016	-0.342	0.296	0.207	-0.304
	Sig. (2-tailed)		0.773	0.886	0.027	0.691	0.942	0.110	0.171	0.344	0.159
	N	23	23	23	23	23	23	23	23	23	23
OM	Correlation Coefficient	-0.064	1.000	0.386	-0.130	0.089	0.181	-.442*	-0.351	0.007	0.078
	Sig. (2-tailed)	0.773		0.069	0.556	0.685	0.408	0.035	0.101	0.976	0.722

		y	OM	QR	TA	BI	CA	OC	EF	CFA	CFT
	N	23	23	23	23	23	23	23	23	23	23
QR	Correlation Coefficient	0.032	0.386	1.000	-0.198	-0.314	0.185	-0.135	-0.259	.430*	0.008
	Sig. (2-tailed)	0.886	0.069		0.366	0.144	0.397	0.539	0.232	0.041	0.972
	N	23	23	23	23	23	23	23	23	23	23
TA	Correlation Coefficient	.461*	-0.130	-0.198	1.000	0.117	0.004	-0.143	.664**	0.175	-0.224
	Sig. (2-tailed)	0.027	0.556	0.366		0.596	0.986	0.515	0.001	0.426	0.304
	N	23	23	23	23	23	23	23	23	23	23
BI	Correlation Coefficient	0.088	0.089	-0.314	0.117	1.000	-0.148	-0.393	0.090	-.518*	-0.177
	Sig. (2-tailed)	0.691	0.685	0.144	0.596		0.499	0.063	0.684	0.011	0.420
	N	23	23	23	23	23	23	23	23	23	23
CA	Correlation Coefficient	-0.016	0.181	0.185	0.004	-0.148	1.000	-0.105	-0.095	-0.027	-0.124
	Sig. (2-tailed)	0.942	0.408	0.397	0.986	0.499		0.634	0.666	0.903	0.572
	N	23	23	23	23	23	23	23	23	23	23
OC	Correlation Coefficient	-0.342	-.442*	-0.135	-0.143	-0.393	-0.105	1.000	0.168	0.175	0.275
	Sig. (2-tailed)	0.110	0.035	0.539	0.515	0.063	0.634		0.443	0.425	0.204
	N	23	23	23	23	23	23	23	23	23	23
EF	Correlation Coefficient	0.296	-0.351	-0.259	.664**	0.090	-0.095	0.168	1.000	0.068	-0.021
	Sig. (2-tailed)	0.171	0.101	0.232	0.001	0.684	0.666	0.443		0.760	0.924
	N	23	23	23	23	23	23	23	23	23	23
CFA	Correlation Coefficient	0.207	0.007	.430*	0.175	-.518*	-0.027	0.175	0.068	1.000	0.146
	Sig. (2-tailed)	0.344	0.976	0.041	0.426	0.011	0.903	0.425	0.760		0.507
	N	23	23	23	23	23	23	23	23	23	23
CFT	Correlation Coefficient	-0.304	0.078	0.008	-0.224	-0.177	-0.124	0.275	-0.021	0.146	1.000
	Sig. (2-tailed)	0.159	0.722	0.972	0.304	0.420	0.572	0.204	0.924	0.507	
	N	23	23	23	23	23	23	23	23	23	23

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Source: (Research data,2023)

The Spearman's rho correlation coefficients matrix in Table 4.11 provides a comprehensive assessment of the relationships among key variables within our research framework. From the results, a significant positive correlation between the application of emerging finance technologies (y) and company size (TA) was identified, a negative correlation between y and Ownership Concentration (OC) was also identified in addition to the CFO's tenure (CFT), exhibiting a negative correlation with the dependent variable, y. Company Profitability (OM)demonstrated a negative correlation with Board Independence (BI) and a positive correlation with the number of employees in the finance function (EF). Company size (TA) further exhibited a significant positive correlation with employees in the finance function (EF). Board Independence (BI) shows displayed a negative association with Ownership Concentration (OC) and CFO Age (CFA). Ownership Concentration (OC) demonstrated a positive correlation with Company size (TA).

4.6.2 Binary Logistic Regression Model

This section presents the results of the regression analysis that answers the second study research question. Section 4.6.2.1 analyzed the goodness of fit of the model whilst section 4.6.2.2 presented an analysis of the binary regression model.

4.6.2.1 Goodness of Fit

In evaluating the goodness of fit for the study model, a comprehensive set of statistical measures to assess the model's overall performance and its ability to adequately capture the underlying data patterns were used. Omnibus Tests of Model Coefficients test is presented under Section 4.6.2.1.1, Cox & Snell R Square is presented in Section 4.6.2.1.2 while the Hosmer and Lemeshow Test is presented under Section 4.6.2.1.3 Collectively, this goodness of fit tests, contributed to a robust evaluation framework, ensuring the reliability and validity of our statistical model.

4.6.2.1.1 Omnibus Test of Model Coefficients

The Omnibus Tests of Model Coefficients provided a global assessment of the model's significance, examining whether any of the predictors significantly contribute to explaining the variance in the dependent variable. This test allowed the researcher to gauge the overall fit of the model and identify whether the combined effect of all predictors was statistically significant. The Omnibus Tests of Model Coefficients involves comparing the observed differences in log-likelihood between a null model (with no predictors) and the model under consideration, utilizing the chi-square distribution. The resulting chi-square statistic and its associated p-value indicate whether the inclusion of predictors significantly improves the model's fit. Interpreting the results involves assessing whether this p-value is below the chosen significance level, often set at 0.05. If the p-value is less than 0.05, it suggests that the model, as a whole, is statistically significant and provides valuable information beyond a null model. Conversely, a p-value exceeding 0.05 implies a lack of evidence to reject the null hypothesis, suggesting that the model may not be significantly different from a null model. Table 4.12 below tabulates the test results for the Omnibus Tests of Model Coefficients.

Table 4.12 Omnibus Tests of Model Coefficients test table

		Chi-square	**df**	**Sig.**
Step 1	Step	8.644	9	0.471
	Block	8.644	9	0.471
	Model	8.644	9	0.471

Source: (Research data,2023)

Table 4.12 provides the outcomes of the Omnibus Tests of Model Coefficients. The chi-square statistic, measuring the discrepancy in log-likelihood between the model and a null model, is reported for Step 1, Block, and the overall Model, all yielding a consistent value of 8.644 with 9 degrees of freedom. The associated p-value across these steps is 0.471. This non-significant p-value suggests that, at the chosen significance level, the predictors included in the logistic regression model do not collectively contribute significantly to explaining the variability in the dependent variable.

4.6.2.1.2 Cox & Snell R Square

The Cox & Snell R Square served as an essential metric for quantifying the proportion of variability in the dependent variable that our model accounted for. This measure offered insights into the goodness of fit by indicating the extent to which the model captured the inherent variability in the observed outcomes. The Cox & Snell R Square is a metric employed in logistic regression to quantify the proportion of variance in the dependent variable that the model can explain. It is calculated by comparing the -2 Log likelihood of the fitted model to that of a null model with no predictors. The formula for Cox & Snell R Square is derived from the likelihood ratio test, providing an estimate of the pseudo-R squared. The interpretation of Cox & Snell R Square is akin to the traditional R-squared in linear regression, representing the proportion of variance explained by the model. Table 4.13 below tabulates the test results for the Cox & Snell R Square.

Table 4.13 Cox & Snell R Square test table

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	15.441[a]	0.313	0.483
a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.			

Source: (Research data,2023)

Table 4.13 presents the results of the performance of the logistic regression model through the Cox & Snell R Square metric. The reported -2 Log likelihood of 15.441 for Step 1 signifies the model's overall fit. The accompanying Cox & Snell R Square of 0.313 suggests that approximately 31.3% of the variability in the dependent variable is accounted for by the selected predictor variables. This moderate level of explained variance indicates the model's effectiveness. The termination of estimation at iteration number 7 due to minimal changes in parameter estimates underscores the stability of the model. These findings collectively illuminate the model's ability to capture a substantial portion of the underlying patterns in the research data.

4.6.2.1.3 Hosmer and Lemeshow Test

The Hosmer and Lemeshow Test scrutinized the model's calibration by comparing observed and predicted probabilities within specific risk groups. This test helped to assess whether the model accurately predicted the outcomes across different levels of risk, providing a crucial evaluation of the model's suitability for practical applications. The Hosmer and Lemeshow test evaluate the agreement between the observed and predicted outcomes by dividing the predicted probabilities into several groups or "bins" and then comparing the observed and expected frequencies within each bin. The chi-square statistic is calculated based on these comparisons, and the degrees of freedom are determined by the number of bins minus the number of estimated parameters in the model. Table 4.14 below tabulates the test results for the Hosmer and Lemeshow Test.

Table 4.14 Hosmer and Lemeshow test table

Step	Chi-square	df	Sig.
1	2.271	8	0.972

Source: (Research data,2023)

Table 4.14 reports the outcomes of the Hosmer and Lemeshow goodness-of-fit test for the logistic regression model in Step 1 of our analysis. The chi-square statistic of 2.271, with 8 degrees of freedom, yields a non-significant p-value of 0.972. The non-significant p-value from the Hosmer and Lemeshow test (0.972) indicates that the logistic regression model, as specified in Step 1, fits the observed data well. Overall, the non-significant result provides a level of confidence in the adequacy of the logistic regression model in representing the observed patterns in the research data.

4.6.2.2 Binary Logistic Regression Model Analysis

A binary logistic regression analysis was used to determine whether company characteristics which had been grouped into three dimensions, namely, company financial metrics, other company features, and finance function features simultaneously influence the dependent variable, of the application of emerging finance technologies. The results of the binary logistic regression model are presented on table 4.15 and 4.16 below.

Table 4.15 Binary Logistic Regression Analysis

Independent variable	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Company Profitability	-.566	3.114	-0.18	.856	-6.668	5.537	
Company Liquidity	.054	.515	0.11	.916	-.955	1.063	
Company Size	.381	.784	0.49	.627	-1.155	1.918	
Board Independence	4.274	6.965	0.61	.539	-9.377	17.926	
Company age	.049	1.543	0.03	.975	-2.976	3.074	

Independent variable	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Ownership concentration	-5.474	9.425	-0.58	.561	-23.947	13	
Number of employees in Finance function	.426	1.469	0.29	.772	-2.453	3.305	
CFO age	2.035	1.844	1.10	.27	-1.579	5.649	
CFO tenure	-1.034	1.081	-0.96	.339	-3.154	1.085	
Independent variable	**Odds Ratio**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Company Profitability	.568	1.768	-0.18	.856	.001	253.832	
Company Liquidity	1.056	.543	0.11	.916	.385	2.896	
Company Size	1.464	1.148	0.49	.627	.315	6.81	
Board Independence	71.82	500.24	0.61	.539	0	60956126	
Company age	1.05	1.621	0.03	.975	.051	21.627	
Ownership concentration	.004	.04	-0.58	.561	0	442269.54	
Number of employees in Finance function	1.531	2.25	0.29	.772	.086	27.258	
CFO age	7.651	14.108	1.10	.27	.206	284.011	
CFO tenure	.355	.384	-0.96	.339	.043	2.96	
Constant	0	.003	-0.51	.608	0	4.732e+10	
Mean dependent var		0.217	SD dependent var			0.422	
Pseudo r-squared		0.359	Number of obs			23	
Chi-square		8.644	Prob > chi2			0.471	
Akaike crit. (AIC)		35.441	Bayesian crit. (BIC)			46.796	

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

Source: (Research data,2023)

Table 4.15 presents the outcomes of a binary logistic regression analysis investigating the impact of company financial metrics (company profitability, liquidity, and size), other company features (Board independence, ownership concentration, and company age), and finance function features (CFO age and Tenure and number of employees in the finance department) on the application of emerging finance technologies. The coefficients (Coef.) represent the estimated log-odds change in the probability of the binary outcome associated with a one-unit change in each respective independent variable. None of the coefficients attained a statistical significance, as indicated by the p-values. Table 4.15 also provides the odds ratios corresponding to each independent variable, indicating the change in odds of technology adoption for a one-unit change in the independent variable. None of the odd's rations attained a statistical significance, as indicated by the p-values.

The model's overall performance is assessed through the pseudo-R-squared (0.359), indicating a moderate level of explanatory power. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) metrics were used for model comparison and selection. In the context of Table 4.18, the AIC and BIC values are presented as 35.441 and 46.796, respectively, lower values of AIC and BIC indicate a better-fitting model, with the minimum values suggesting the most parsimonious and effective representation of the data, the AIC value of 35.441 and BIC value of 46.796 suggest a reasonable fit of the logistic regression model.

4.7 Primary data from the questionnaire

This section presents a summary of qualitative factors on the adoption of emerging finance technologies. Highly structured questionnaires were used to collect primary data to enable an assessment of qualitative factors that impact the adoption of emerging technologies in the finance department of non-financial companies listed in the NSE. Section 4.7.1 highlights the complexity of the current technology landscape and the level of automation of finance department processes whilst section 4.7.2 presents some of the challenges and opportunities encountered in the adoption of emerging technologies.

4.7.1 Current Technology Landscape and Automation Finance Department Processes.

Table 4.16 below presents descriptive statistics on the current technology landscape of finance departments of non-financial companies listed in the NSE.

Table 4.16 Current Technology Landscape.

Current Technology landscape	Frequency	Percentage
Number of Financial Operations and Reporting applications in use in the finance department		
1	8	34.8%
2-3	13	56.5%
4 & above	2	8.7%

Current Technology landscape	Frequency	Percentage
Total	**23**	**100.0%**
Interface between Applications in use by the Finance Department		
All applications are automatically interfaced	13	56.5%
Some applications are automatically interfaced	4	17.4%
There are no automated interfaces	6	26.1%
Total	**23**	**100.0%**
Reasons why applications are not interfaced		
Incompatible applications	10	43.5%
all applications are automatically interfaced	13	56.5%
Total	**23**	**100.0%**

Source: (Research data,2023)

56.5% of the non-financial companies listed on the NSE use 2-3 financial operations and reporting applications, while 8.7% use four or more applications and 34.8% use only one application. 56.5% of the finance department's applications are automatically interfaced which implies a relatively high level of automation in data exchange and communication between different applications while 26.1% of respondents reported having no automated interfaces, implying that manual intervention or non-automated methods may be used for data exchange for these companies. 43.5% of the respondents cited incompatibility of applications for the absence of interfaces, highlighting that financial applications do not seamlessly integrate due to differences in technology, data formats, or other factors.

Table 4.17 below presents descriptive statistics on the level of automation of finance department processes in the form of mean and standard deviation.

Table 4.17 Level of automation of finance department processes.

Level of automation of Finance Department Process	N	Mean	Standard Deviation
The Procure to Pay is highly automated	23	3.67	1.371
The Invoice to Cash is highly automated	23	4.00	1.206
The Record to Report is highly automated	23	3.50	1.000
Financial Planning and Analysis is highly automated	23	3.25	1.055
The Statutory to Tax is highly automated	23	3.25	0.965
The Fixed Assets Process is highly automated	23	3.58	1.311
The Payroll & Benefits Process is highly automated.	23	4.00	0.953

Source: (Research data,2023)

The Invoice to Cash and Payroll & Benefits have mean values of 4 implying that a majority of non-financial companies listed in the NSE have invested and successfully implemented automation of these processes, furthermore, the lower standard deviations of 1.206 and 0.953 imply a higher level of consensus among respondents regarding the perceived automation in these processes. The Financial Planning and Analysis and Statutory to Tax have the lowest mean values of 3.25 which may imply that companies face challenges or have not prioritized extensive automation in these areas.

4.7.2 Qualitative Trends in the Adoption of Emerging Technologies.

This section presents some qualitative trends on the adoption of emerging technologies.

Table 4.18 Level of automation of finance department processes.

Trends in adoption of emerging technologies	RPA		Machine Learning		AI		Blockchain	
	Freq	%	Freq	%	Freq	%	Freq	%
First year technology was used								
2021	2	8.7	2	8.7	2	8.7	-	-
2022	2	8.7	-	-	-	-	-	-
NA	19	82.6	21	91.3	21	91.3	23	100.0
Total	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**

Trends in adoption of emerging technologies	RPA		Machine Learning		AI		Blockchain	
Who developed the technology								
Local supplier	2	8.7	-	-			-	-
Foreign supplier	2	8.7	2	8.7	2	8.7	-	-
NA	19	82.6	21	91.3	21	91.3	23	100.0
Total	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**
Why is the technology not in use								
Adopted	4	17.4	2	8.7	2	8.7	-	-
Inadequate IT infrastructure	2	8.7	2	8.7	2	8.7	-	-
Lack of awareness of functionality	10	43.5	11	47.8	10	43.5	10	43.5
Lack of skills in the technology	2	8.7	2	8.7	4	17.4	6	26.1
Other	6	26.1	6	26.1	5	21.7	7	30.4
Total	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**
Opportunities identified for implementation								
Adopted	4	17.4	2	8.7	2	8.7	-	-
None	9	39.1	15	65.2	17	73.9	17	73.9
Yes (1–5 years plan)	4	17.4	4	17.4	2	8.7	4	17.4
Yes (over 5 years plan)	6	26.1	2	8.7	2	8.7	2	8.7
Total	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**	**23**	**100.0**

Source: (Research data,2023)

The non-financial companies listed in the NSE started to implement the emerging technologies in the year 2021, with 8.7% of the respondents implementing RPA, AI, and Machine learning in 2021 and 8.7% adopting RPA in 2022. RPA has been implemented by both local and foreign suppliers while machine learning and AI has only been implemented by foreign suppliers. Majority of the respondents identified lack of the awareness of the functionalities of the emerging technologies as the reason for not adopting the emerging technologies and other reasons for not implementing the technologies were Inadequate IT infrastructure and lack of skills in the market for use of these technologies. Majority of the Companies have also not identified any opportunities for the adoption of the emerging technologies.

4.8 Chapter Summary

The chapter presented data and study results from the primary data that was collected through questionnaires and secondary data that was collected from the annual in the annual audited financial statements that are published and submitted to the Capital Markets Authority. Descriptive statistics, diagnostic tests, correlation, and regression analysis were performed, and the results were presented. The next chapter provides details on the discussions, conclusions, and recommendations based on the study results presented in this chapter.

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a discussion of the findings under section 5.2 based on the objectives of the study, conclusions from the study in under section 5.3, while the recommendations from the study are outlined in section 5.4 and the limitations and suggestions for further research in future studies in section 5.5.

5.2 Discussions

This section outlines a discussion of the study findings that were presented in chapter four concerning the study title, Factors Influencing the Adoption of Emerging Technologies in Finance Functions; Case of Non-Financial Companies Listed in Kenya. These discussions were based on the objectives that the study aimed to achieve.

5.2.1 To identify the effect of company specific characteristics on the adoption of emerging technologies in the finance functions of listed non-financial companies in the NSE

The study investigated the relationship between company financial metrics (company profitability, liquidity, and size), other company features (Board independence, ownership concentration, and company age), and finance function features (CFO age and Tenure and number of employees in the finance department) and the application of emerging finance technologies in non-financial companies listed on the NSE. The relationship between these company features, and the adaptation of emerging finance technologies is outlined in the following section.

5.2.2.1 Company Profitability

The findings of the study revealed that company profitability had a negative, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the negative co-efficient of -0.566 and P value of 0.856. This finding aligns with the findings of Pavlatos and Kostakis (2018), who found that those organizations that had low profitability in the past adopted and used new technologies more extensively, to improve their financial performance in the future, in addition

Plaschke, et al. (2018), postulated that emerging technologies are used to automate the finance departments in a bid to gain a competitive advantage by lowering their administrative overheads and other efficiencies gained from automation.

5.2.2.2 Company Liquidity

The results of the study demonstrated that company liquidity had a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 0.054 and P value of 0.916. This finding contradicts Khlifi (2022) who found that when the liquidity ratio is low, companies are more likely to adopt Internet financial reporting tools. The results of this finding are not surprising as Amihud and Levi (2023), found that Illiquidity raises a firm's cost of capital, therefore resulting in lower investment in capital assets, R&D, and inventory, therefore buttressing the finding that higher liquidity levels would result in the adoption of emerging technologies which require capital outlays.

5.2.2.3 Company Size

The results of the study revealed that company size had a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 0.381 and P value of 0.627. This finding aligns with the findings of Bosman et al. (2020), who found that firms that are large in size prioritize enterprise support operations technologies which are tools designed to streamline and enhance support operations within an enterprise. This result is considered reasonable as companies that are larger in size have more transactions as well as processes which can be simplified and made more efficient by the emerging finance technologies.

5.2.2.4 Board Independence

The study showed that board independence had a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 4.274 and P value of 0.539. According to Faghani and Gyapong (2019) board independence positively influenced the implementation of new legislation, furthermore Tulung and Ramdani (2018), found that board independence positively influenced the performance of companies. High board independence is therefore likely to influence the adoption of emerging technologies positively due to the expectation that the emerging technologies also result in improved performance and additional competitive advantage.

5.2.2.5 Company age

Company age has a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 0.49 and P value of 0.975. According to Yulyan et al. (2017) company age positively influences the Implementation of automated Integrated Reporting, the higher the age of the company, the higher the likelihood of implementation of automated Integrated Reporting. This result is not surprising because companies that have been listed for longer periods of time are expected to be stable and therefore can invest in new technologies aimed at improving their performance.

5.2.2.6 Ownership concentration

The findings of the study revealed that ownership concentration had a negative, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the negative co-efficient of -5.474 and P value of 0.561. Faghani and Gyapong (2019) found that ownership concentration negatively influenced the implementation of new legislation and therefore the study aligns with their findings. Adoption of emerging technologies has some inherent risk of success and therefore it can be derived that where ownership concentration is high, there is a higher risk exposure for the owners which would result in a lower risk appetite to invest in the emerging technologies.

5.2.2.7 Number of employees in Finance function

The number of employees in the finance function as measured by the natural log of the number of employees in the finance department has a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 0.426 and P value of 0.772. This finding aligns with the findings of Ilin et al. (2021), who found that firms that are more likely to adopt e-business in enterprise resource planning. This finding is further buttressed by the commonly held belief that larger firms have more resources to commit to required investments due to the larger pool of human resources and skill set.

5.2.2.8 CFO age

The study showed that CFO age had a positive, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of 2.035 and P value of 0.27. Ginesti et al. (2021), found that older CFOs were positively associated with the intensity of R&D investment, therefore aligning with the results of this study. This result was surprising because the expectation was that the younger CFOs are more technology savvy and would be more poised to implement emerging technologies, however, the result is justified by the fact that older CFOs have more experience and are therefore likely to take more calculated risks in implementing emerging technologies to improve company performance.

5.2.2.9 CFO tenure

The CFO tenure as measured by the natural log of length of service as the CFO has a negative, non-significant relationship with the adoption of emerging finance technologies as demonstrated by the positive co-efficient of -1.034 and P value of 0.339. This finding aligns with the findings of Hiebl et al. (2017), who found that CFO tenure is also negatively associated with enterprise resource planning (ERP) system adoption. This finding can be justified by the fact that longer-tenured CFOs are also less likely to foster major IT investment because often they are at a comfort level where the current systems are working as expected and they would therefore not want to disturb the status quo.

5.2.2 To assess the level of usage and the type of emerging technologies adopted in the finance function of listed non-financial companies in the NSE.

The findings indicated that the level of usage of emerging technologies in the finance function of listed non-financial companies in the NSE is at the initial phase of development with only 21.7% of the listed non-financial companies in the NSE having adopted the use of the emerging finance technologies. These findings align with the findings of Truant et al. (2021), who highlighted that the adoption of digital tools to support daily company operations was still at the embryonic stage in Italian-listed companies. The findings also indicated that companies started to adopt the emerging finance technologies during the year ended 31 December 2021, these findings reinforce the findings of Tut (2023) who concluded that the pandemic accelerated the adoption and increased concentration of Financial Technology in Kenya. The results further showed that RPA had the highest level of adoption at 17.4% whilst blockchain had not been adopted by any of the Companies and that none of the companies in the Agricultural and Energy and Petroleum industries had adopted the emerging finance technologies in contrast, all the companies in the Telecommunication & Technology and Automobiles & Accessories industries had full usage of emerging technologies.

According to Agarwal and Shroff (2021), some of the prerequisites for companies to adopt emerging finance technologies include end-to-end digitized and transformed processes, aggregation of data at the organizational level, investment in foundational tools and technologies, and availability of talent. According to the primary data collected, only 34.8% of the companies use one accounting application in the finance department and where more than one accounting application was in use, only 56.5% of the applications were automatically interfaced with 43.5% of respondents citing that the applications were not interfaced due to incompatible applications. Additionally, most of the finance department processes were not automated with the Financial Planning and Analysis and Statutory to Tax processes having low automation levels, further, the majority of respondents cited a lack of skills in emerging technologies as barriers to implementation of the emerging technologies. The low level of usage of emerging technologies can therefore be explained by the low investment in the prerequisite technologies and skills that are required to implement the emerging finance technologies. CFOs therefore need to invest in the prerequisite technologies and skills.

5.2.3 To identify opportunities for the adoption of emerging technologies and challenges that hinder the adoption of the emerging technologies by finance departments of listed non-financial companies in the NSE.

To determine whether non-financial companies listed in the NSE had identified opportunities for the application of emerging technologies and challenges that hindered the adoption of the emerging technologies by finance departments, a structured questionnaire was issued to the respondents. The results of the study showed that a significant majority of respondents had not identified opportunities for the adoption of emerging technologies in the finance department. 73.9% of respondents had not identified any opportunities for the adoption of AI and Blockchain whilst 65.2% of respondents had not identified any opportunities for the adoption of machine learning. 17.4% of respondents had identified opportunities to implement RPA in short-term plans while 26.1% had identified opportunities to implement RPA in longer-term plans. The low adaptation rates are connected to the implementation challenges that have been identified which relate to inadequate IT infrastructure, lack of awareness in functionalities as well as lack of skills in the market for use of the technologies. These challenges would require significant investments by the companies to upgrade IT infrastructure and the skillset of employees to reap the significant benefits that can be achieved from adoption of the emerging finance technologies.

5.3 Conclusions

In conclusion, the study aimed at assessing the level of usage of emerging technologies in the finance function of listed non-financial companies in the NSE, identifying company features and the type of emerging technologies adopted by the finance functions of listed non-financial companies in the NSE and to identify opportunities for the application of emerging technologies and challenges that hinder the adoption of the emerging technologies by finance departments of listed non-financial companies in the NSE. The findings indicated that the level of usage of emerging technologies in the finance function of listed non-financial companies in the NSE is at the initial phase of development with only 21.7% of the listed non-financial companies in the NSE having adopted the use of the emerging finance technologies. The results of the binary logistic regression model analysis found that company profitability, ownership concentration and ownership concentration and CFO tenure had a negative, relationship with the adoption of emerging finance technologies whilst company liquidity, size age, board independence, number of employees in the finance department and CFO age had a positive relationship with the adoption of emerging finance technologies. None of the independent variables had a significant relationship with the adoption of the emerging finance technologies. The conclusion that no significant relationships exist between the independent variables and the adoption of emerging finance technologies is supported by the robustness of the analysis, accounting for a comprehensive set of variables and a sufficiently sized sample. The findings remain consistent across various model specifications and demonstrate a high degree of reliability, contributing to the overall validity of the thesis conclusion. The conclusion that no significant relationships exist between the independent variables and the adoption of emerging finance technologies is supported by the robustness of the analysis, accounting for a comprehensive set of variables and a sufficiently sized sample. The findings remain consistent across various model specifications and demonstrate a high degree of reliability, contributing to the overall validity of the thesis conclusion. The also study revealed a significant lack of enthusiasm among listed non-financial companies to identify opportunities for adopting emerging finance technologies, citing challenges such as insufficient IT infrastructure, limited awareness of functionalities, and a skills gap, necessitating substantial investments for reaping potential benefits. This research contributes to the literature on technological innovation and breaks new ground by focusing on non-financial companies listed on the NSE. Studies analyzing the influence of technological innovation have mostly focused on financial companies.

5.4 Recommendations

For non-financial companies listed in the NSE to adopt emerging finance technologies that would enable them to gain a competitive advantage, the study recommends that the companies invest in end-to-end digitization of companywide processes and in foundational tools and technologies that will enable aggregation of data at the organizational level so that the emerging technologies can work efficiently. The study also identified a significant gap in the skillset required to develop and implement emerging technologies, finance professionals and academics therefore need to upskill in Finance IT and further curriculum developers need to introduce relevant curricula that will fill the skill gap. The study also recommends that regulators perform capacity building for local companies that can build emerging finance technologies by offering incentives for entry into the industry which will accelerate the growth of the industry.

5.5 Limitations and Suggestions for further research

Despite the contributions of this study, some limitations should be addressed in future research. Firstly, the study was limited to non-financial companies listed in the NSE, and therefore the findings may not be generalizable to privately held non-financial companies.

Secondly, to collect the primary data, the study utilized a structured questionnaire which may not have captured all the qualitative data that would have assisted in providing additional context on the understanding of opportunities and challenges in the adoption of emerging technologies, the use of interviews in addition to the structured questionnaires would have presented this additional qualitative context. Finally, the study did not investigate the role of cultural factors in the adoption of emerging technologies. Cultural factors include the attitude towards innovation, trust, time orientation as well as risk aversion or profiling.

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Appendix I: Introductory letter

Dear Respondent,

We are conducting a research study to assess the application of emerging technologies in the finance function of listed non-financial companies in the NSE. As a finance director or equivalent position, your insight and experience would be invaluable in helping us understand the current landscape and the level of automation of finance processes.

The objective of this study is to identify company features, the types of emerging technologies adopted by finance functions of listed non-financial companies in the NSE, and the opportunities and challenges hindering the adaptation of emerging technologies. Your participation in this study would be highly appreciated.

The questionnaire consists of three sections and will take approximately 15 minutes to complete. All responses will be kept confidential and anonymous. Your cooperation and time in completing this questionnaire are greatly appreciated. If you have any questions, please do not hesitate to contact us.

Sincerely, [Researcher Name & Affiliation]

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.

SECTION A – COMPANY PROFILE

1. Name of the organization: ______________________________

2. Contact person: ______________________________

3. Position held: ______________________________

4. For how many years has the Company been listed in the Nairobi Securities Exchange?

   ____

5. In your opinion, is the Company generally open to the incorporation of emerging technologies?

   (Where 1 is Strongly Disagree; 2 is Disagree; 3 is Somewhat Agree; 4 is Agree and 5 is Strongly Agree)

Scale	**1**	**2**	**3**	**4**	**5**
Response					

SECTION B – FINANCE FUNCTION PROFILE

1. How many permanent/full-time individuals work in the Finance Department?

   ____

2. Age of the CFO/Finance Director

   a) below 45 years ( )

   b) 45 years and above ( )

3. What is the current tenure (Years of service) of the CFO/Finance Director

   ____

4. How is the Finance Department structured?

   a) By process (e.g., treasury) ( )

   b) By physical location ( )

   c) By customer segment ( )

   d) By production segment ( )

   e) By Company (e.g., subsidiary) ( )

   f) Other ( )

5. How many finance applications are used in the finance department?

   a) 0 (manual systems in place) ( )

   b) 1 ( )

   c) 2 -3 ( )

   d) 4 -5 ( )

   e) 5 and above ( )

6. If the Company uses more than 1 finance application, do the applications automatically interface with the main Finance Application?
   a) all applications are automatically interfaced ( )
   b) some applications are automatically interfaced ( )
   c) there are no automated interfaces ( )

7. Why are the applications not automatically interfaced?
   a) Cost – too expensive ( )
   b) Incompatible applications ( )
   c) Data security ( )
   d) Other ( )

8. Automation of finance processes
   Please indicate the extent to which you disagree or agree with the following statements about the automation of finance processes by ticking in the appropriate space.
   (Where 1 is Strongly Disagree; 2 is Disagree; 3 is Somewhat Agree; 4 is Agree and 5 is Strongly Agree)
   Automation refers to the use of technology to perform tasks without the need for human intervention. This can include the use of machines, algorithms, and software to automate manual processes, reduce errors, and increase efficiency.

Statement	1	2	3	4	5
The Procure to Pay (P2P) process is highly automated. *The P2P process encompasses all activities involved in acquiring goods and services from external suppliers, from requisition to payment.*					

Statement	**1**	**2**	**3**	**4**	**5**
The Invoice to Cash (I2C) process is highly automated. *The I2C process encompasses all activities involved in the billing of a customer and the receipt of payment for goods or services provided.*					
The Record to Report (R2R) Process is highly automated. *The R2R process involves the collection, consolidation, and dissemination of financial information used to produce a company's financial statements. The goal of R2R is to provide accurate, timely, and relevant financial information to stakeholders, including management, investors, and regulatory agencies.*					
Financial Planning and Analysis (FP&A) is highly automated. *The FP&A process helps organizations make informed decisions about their financial future by analyzing past and present financial data, forecasting future financial performance, and providing actionable insight*					
The Statutory to Tax (S2T) Reporting process is highly automated. *The S2T process involves preparing and filing tax returns for an organization in compliance with the tax laws and regulations of the jurisdiction in which it operates.*					
The Fixed Assets Process is highly automated *The Fixed Assets Process refers to* the *procedures and processes involved in managing and accounting*					

Statement	1	2	3	4	5
for an organization's long-term tangible assets, such as property, equipment, and machinery.					
The Payroll & Benefits Process is highly automated *The Payroll and Benefits Process refers to the procedures and processes involved in managing and administering an organization's payroll and employee benefits*					

SECTION C – APPLICATION OF EMERGING TECHNOLOGIES

A. Robotic Process Automation ("RPA") refers to the automation of tasks that were previously performed by humans through configuring the software to do the work. RPA technologies can be used to send e-mails, record data, and complete spreadsheets and can therefore be used to automate processes ranging from simple data processing tasks such as data entry and processing, bank statement reconciliation, and payment processing to complex tasks such as budgeting and forecasting and financial planning and analysis.

1. Does the Company currently use Robotic Process Automation for finance and accounting business processes? (If the Answer is No please go to question 5)

   Yes ☐

   No ☐

2. In which year in which this technology first used? ______________________

3. How did the company develop RPA? (Tick one of the following)

   a) Purchased from a local supplier ( )
   b) Purchased from a foreign supplier ( )
   c) Developed and implemented in-house by this Company ( )
   d) Developed and implemented in collaboration with a local supplier ( )

e) Developed and implemented in collaboration with a foreign supplier ( )

4. For which of the following reasons does this Company not use RPA?

   a) Lack of capital for investment
   b) Lack of awareness of RPA functionalities
   c) Lack of skills in using RPA
   d) Inadequate or incompatible IT infrastructure
   e) Other

5. The company identified opportunities for the implementation of RPA.

   Yes, in short-term plans (1–5-year plan) ☐

   Yes, in long-term plans (Over 5-year plan) ☐

   No ☐

B. Machine learning is the ability of computers to operate without being explicitly programmed through the application of a series of statistical techniques to conduct self-learning activities from a dataset to perform specified tasks without being programmed to do so. Machine Learning can be used to improve processes such as fraud detection and processing of payments across the finance function.

1. Does the Company currently use machine learning for the automation of finance and accounting business processes? (If the answer is NO, please go to question 5)

   Yes ☐

   No ☐

2. In which year in which this technology first used? ______________________

3. How did the company develop machine learning? (Tick one of the following)

a) Purchased from a local supplier ( )
b) Purchased from a foreign supplier ( )
c) Developed and implemented in-house by this Company ( )
d) Developed and implemented in collaboration with a local supplier ( )
e) Developed and implemented in collaboration with a foreign supplier ( )

4. For which of the following reasons does this Company not use machine learning?

    a) Lack of capital for investment
    b) Lack of awareness of machine learning functionalities
    c) Lack of skills in using machine learning
    d) Inadequate or incompatible IT infrastructure
    e) Other

5. The company identified opportunities for the implementation of machine learning.

    Yes, in short-term plans (1–5-year plan) ☐
    Yes, in long-term plans (Over 5-year plan) ☐
    No ☐

C. Blockchain is a technology that is concerned with the transfer of ownership of assets whilst maintaining a ledger of accurate financial information and has the potential to enhance the accounting profession by reducing the costs of maintaining and reconciling ledgers and providing absolute certainty over the ownership and history of assets.

1. Does the Company currently use blockchain for the automation of finance and accounting business processes? (If the answer is NO, please go to question 5)

    Yes ☐
    No ☐

2. In which year in which this technology first used? ______________________

3. How did the company develop blockchain? (Tick one of the following)

   a) Purchased from a local supplier ( )
   b) Purchased from a foreign supplier ( )
   c) Developed and implemented in-house by this Company ( )
   d) Developed and implemented in collaboration with a local supplier ( )
   e) Developed and implemented in collaboration with a foreign supplier ( )

4. For which of the following reasons does this Company not use blockchain?

   a) Lack of capital for investment
   b) Lack of awareness of blockchain functionalities
   c) Lack of skills in using blockchain
   d) Inadequate or incompatible IT infrastructure
   e) Other

5. The company identified opportunities for the implementation of blockchain.

   Yes, in short-term plans (1–5-year plan) ☐
   Yes, in long-term plans (Over 5-year plan) ☐
   No ☐

D. Artificial intelligence (AI) 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. AI can be applied in accounting and finance in a variety of ways such as optimizing budgeting and forecasting processes using algorithms to scrutinize historical data and identify patterns that can be incorporated to improve forecasts.

1. Does the Company currently use artificial intelligence for the automation of finance and accounting business processes? (If the answer is NO, please go to question 5)

Yes ☐

No ☐

2. In which year in which this technology first used? ____________________

3. How did the company develop AI? (Tick one of the following)

   a) Purchased from a local supplier ( )
   b) Purchased from a foreign supplier ( )
   c) Developed and implemented in-house by this Company ( )
   d) Developed and implemented in collaboration with a local supplier ( )
   e) Developed and implemented in collaboration with a foreign supplier ( )

4. For which of the following reasons does this Company not use AI?

   a) Lack of capital for investment
   b) Lack of awareness of AI functionalities
   c) Lack of skills in using AI
   d) Inadequate or incompatible IT infrastructure
   e) Other

5. The company identified opportunities for the implementation of AI.

   Yes, in short-term plans (1–5-year plan) ☐
   Yes, in long-term plans (Over 5-year plan) ☐
   No ☐

Appendix III: Nairobi Securities Exchange Listed Companies

Table 3: Nairobi Securities Exchange Listed Companies as of December 2022

AGRICULTURAL
Eaagads Ltd
Kakuzi Plc
Kapchorua Tea Kenya Plc
The Limuru Tea Co. Plc
Sasini Plc
Williamson Tea Kenya Plc
AUTOMOBILES & ACCESSORIES
Car & General (K) Ltd
COMMERCIAL AND SERVICES
Eveready East Africa Ltd
Express Kenya Plc
Homeboyz Entertainment Plc
Longhorn Publishers Plc
Nairobi Business Ventures Plc
Nation Media Group Plc
Sameer Africa Plc
Standard Group Plc
TPS Eastern Africa Ltd
Uchumi Supermarkets Plc
WPP Scangroup Plc Ord
CONSTRUCTION & ALLIED
Bamburi Cement Plc
Crown Paints Kenya Plc
E.A. Cables Ltd Ord
E.A. Portland Cement Co. Ltd
ENERGY & PETROLEUM
KenGen Co. Plc
Kenya Power & Lighting Co Plc
TotalEnergies Marketing Kenya Plc

Umeme Ltd
MANUFACTURING & ALLIED
B.O.C Kenya Plc
British American Tobacco Kenya Plc
Carbacid Investments Plc
East African Breweries Plc
Flame Tree Group Holdings Ltd
Kenya Orchards Ltd
Unga Group Ltd
TELECOMMUNICATION & TECHNOLOGY
Safaricom Plc

Appendix IV: Research Budget

Item	**Unit**	**Cost (Kshs)**	**Actual (Kshs)**
Printing and photocopying of proposal	Item	2,000	1,875
Research assistants	2	60,000	60,000
Data analysis	Item	20,000	20,000
Traveling expenses	Item	20,000	14,000
Hard cover binding	3 Copies	3,000	To be incurred
Miscellaneous	Item	19,000	Airtime of 2,000 Stationeries 700 Printing 2,500
Total		**124,000**	

Appendix V: Research License

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **879737** Date of Issue: **20/September/2023**

RESEARCH LICENSE

This is to Certify that Mr.. Paul N Kebati of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: Factors Influencing the Adoption of Emerging Technologies in Finance Functions; Case of Non-Financial Companies Listed in Kenya for the period ending : 20/September/2024.

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879737

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See overleaf for conditions

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Strathmore
UNIVERSITY
BUSINESS SCHOOL

11th September 2023

To Whom It May Concern,

RE: FACILITATION OF RESEARCH – PAUL KEBATI.

This is to introduce Paul Kebati who is a Master of Commerce (MCOM) Student at Strathmore University Business School, admission number MCOM/36619. As part of our MCOM Programme, Paul is expected to do applied research and undertake a project. This is in partial fulfilment of the requirements of the MCOM course. To this effect, Paul would like to request appropriate data from your organization.

Paul is undertaking a research paper on "**Factors Influencing the Adoption of Emerging Technologies in Finance Functions; Case of Non-Financial Companies Listed in Kenya.**" The information obtained shall be treated confidentially and shall be used for academic purposes only.

Our MCOM Programme seeks to establish links with industry, and one of these ways is by directing our research to areas that would be of direct use to industry. We would be glad to share our findings with you after the research, and we trust that you will find them of great interest and of practical value to your organization.

We appreciate your support and shall be willing to provide any further information if required.

Yours sincerely,

Njoki Kiagiri
Manager – Graduate Programmes
Strathmore University Business School.

Strathmore Business School is a Proud member of:

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