ARTIFICIAL INTELLIGENCE-BASED BUSINESS MODELS AND FINANCIAL PERFORMANCE OF LISTED FIRMS IN THE NAIROBI SECURITIES EXCHANGE

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STUDENT'S DECLARATION

I, the undersigned declare that this is my original work and that it has not been submitted to any other College, Institution, or University other than the Catholic University of Eastern Africa for academic purposes.

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ABSTRACT

AI enables a systematic mechanism which allows businesses to gather more valuable and updated data to carry out accurate evaluation of market environment and internal operations simultaneously. AI is thus advantageous to firms as it allows them to apply AI driven decision making on sales and credit forecast. However, despite the growth of opportunities associated with the use of AI, external factors and market volatility pose significant risks to the performance of firms listed at NSE. The investigation thus sought to determine the effect of AI-based business models on financial performance of listed entities in NSE. Specifically, the study determined the effect of AI-based predictive financial modelling, AI-based risk management, AI-based portfolio optimization and AI-based fraud detection on financial performance of listed firms in NSE. The investigation was anchored on diffusion of innovation theory, Technology-Organization-Environment and technology acceptance model. Positivism was employed with correlational research design as the study design. The target population of were the 17 financial firms listed at NSE. Listed firms were the unit of analysis while the unit of observation were the heads of marketing departments, business development department, human resource departments and operations department within the 17 financial firms listed at NSE. Since the target population is relatively small, the investigation conducted a census of all the respondents. Structured questionnaire was to collect primary data. SPSS software was used in the analysis of data. Data analyses involved both descriptive and inferential outcomes which were presented in form of tables and charts. Inferential analysis included correlation and multiple regression analysis. From the results, the investigation established that AI-Based predictive financial modelling showed a positive and significant effect on financial performance (0.321, 0.000<0.05), AI-Based risk management showed a positive and significant effect on financial performance (0.472, 0.000<0.05), AI-Based portfolio optimization showed a positive and significant effect on financial performance (0.420, 0.000<0.05) and AI-Based fraud detection showed a positive and significant effect on financial performance of firms listed at NSE (0.401<0.05). The investigation recommends that the firms listed at NSE ought to adopt AI-based predictive financial modelling as a strategic priority to enhance their financial performance as it improves the accuracy and timeliness of forecasting, budgeting and investment decisions. The listed firms under study should also prioritize the integration of AI-based risk management systems to strengthen their financial performance. The firms under study should also adopt AI-based portfolio optimization tools to enhance financial performance as it maximizes returns while effectively managing risk across diverse asset classes. The listed firms under investigation should implement AI-based fraud detection systems to strengthen financial performance. The study further recommends that ought to develop a supportive regulatory framework that encourages the adoption of AI-Business models by the listed firms under study to enhance performance.

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ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AIDP	Artificial Intelligence Development Plan
BDA	Big Data Analytics
EABL	East African Breweries Limited
GDP	Gross Domestic Product
IoT	Internet of Things
IT	Information Technology
NACOSTI	National Commission for Science, Technology and Innovation
NPLs	Non-Performing Loans
NSE	Nairobi Securities Exchange
R&D	Research and Development
ROA	Return on Assets
ROE	Return on Equity
SCRM	Supply Chain Risk Management
SMEs	Small and Medium Enterprises
SPCR	Stock Price Cash Risk
TOE	Technology-Organization-Environment Framework

OPERATIONAL DEFINITION OF TERMS

AI-Based Business Models: Refers to the strategies that integrate AI technologies into core operations, products or services to create value, optimize efficiency and drive competitive advantage (Mishra & Tripathi, 2021).

AI-Based Predictive Financial Modelling: Entails the use of AI algorithms to analyze historical and real-time financial data in order to forecast future financial outcomes (Faheem et al., 2024).

AI-Based Risk Management: The application of AI technologies to identify, assess and mitigate financial and operational risks through data-driven insights and real-time analysis (Alonge et al., 2023).

AI-Based Portfolio Optimization: Entails the use of AI algorithms to allocate assets efficiently by analyzing vast datasets, predicting market trends and balancing risk and return to enhance investment performance (Olanrewaju, 2025).

AI-Based Fraud Detection: Refers to the use of AI to automatically identify, monitor and prevent fraudulent activities by detecting anomalies and patterns in financial data (Faisal et al., 2024).

Financial Performance: Refers to the measurement of its profitability, revenue generation and cost efficiency over a specific period, usually one year (Umoh, 2024).

CHAPTER ONE

INTRODUCTION

1.0 Introduction to the Study

The chapter lays the study's background which is structured to include the description of AI-based business models, financial performance as well as description of listed firms at NSE. Moreover, the chapter presents the problem statement that motivates this study, research objectives and questions. Further, the chapter proceeds to provide the study significance to practice, policy and future studies, study scope and delimitations. It ends with a brief conceptual and theoretical framework.

1.1 Background to the Study

The financial performance of listed firms is significant in increasing the value of firms and hence boosting the expansion across all the economic sectors accelerating the expansion of the country's economy (Surya et al., 2021). The performance of listed firms is influenced by various economic, regulatory, and market factors. The key performance indicators for the listed firms include return on investment, stock price trends, profitability and revenue growth. The performance of the listed firms in significantly influenced by interest rates, exchange rate fluctuations and inflation, as they influence consumer spending, production costs, and investment levels (Aayale et al., 2022).

Stock returns of the listed firms provide insights into the performance of investments in a particular company over time. Globally, stock returns are significant components of performance of publicly traded entities in US, China and UK. The share returns of these companies are closely monitored by investors and analysts as an indicator of the health of the identified economies (Kilonzo, 2023). Profitability assesses how effectively a company can convert its revenue or sales into earnings or profits, which are crucial for sustaining and growing the business (Zopounidis & Lemonakis, 2024). Stock price performance reflects the

overall financial performance, market valuation and investor confidence of the listed firms. Rising stock prices presents a sign of effective management of the firm as well as strong earning potential whereas declining stock prices may be a signal of poor weak prospects (Vuong, 2022).

A key financial metric that can be applied in evaluating financial health and performance of a firm is its profitability as it provides the effectiveness, efficiency as well as the entity's overall financial strength. Increased profitability is a resultant of higher share returns because it indicates that a firm is generating strong returns on its investments (Desmita & Sihombing, 2024). High profitability enables the listed firms attract new investors as it boosts investor confidence. There are negative factors that affect profitability of the firms including fluctuations in foreign exchange rates, taxation as well as inflation (Pangestuti et al., 2022).

Revenue growth of the listed firms is an indicator of the ability of the firms to increase sales as well as expand its share in the market over time. Enhanced growth in revenues can be enhanced through market expansion, innovation as well as diversification (Vuković et al., 2022). The growth of revenues of the listed firms attracts more investors signaling higher shareholder value and profitability. Innovation of new products signals the ability of the firms to be competitive as well as adapting to the dynamic business environment. The introduction of new products in the market enhances the profitability of the firms as a result of expanded market and enhanced customer engagement (Handayani & Rahayu, 2019).

With the current competitive and highly evolved environments, businesses struggle to find smart systems and best solutions to navigate these dynamic environments. Businesses should be increasingly adaptable and innovative to respond to evolving customer needs, market dynamics as well as be proficient in utilizing advanced business systems. This includes utilizing the potential of new sophisticated technologies to collect the requested data and analyse them accurately and quickly (Rrucaj, 2023). Artificial intelligence is increasingly

being considered a smart solution that can contribute to organization understanding of their internal and external factors, leading to improved decision-making (Olan et al., 2022).

AI entails a general term involving the use of a computer to model intelligent behavior with minimal human intervention (Shneiderman, 2020). AI enables a systematic mechanism whereby businesses are able to collect more updated and valuable data that help conduct an accurate evaluation of internal operations and the market environment simultaneously (Rane et al., 2024). This helps these business entities to improve business decisions quality. Approximately 89% of global organizations expressed a strong feeling that companies failing to adopt AI smart applications would suffer losses in market share and competitive momentum (Baabdullah, 2024). The successful adoption of AI is largely reliant on key capabilities of organizations. The effective use of AI in high-quality decision-making depends on how much employees negatively or positively value AI systems in the decision-making process (Al-Surmi et al., 2022).

AI technologies are advantageous to business entities as it transforms their operations including the application of AI in making decisions to forecast sales and credit defaults. Furthermore, AI can provide significant benefits by automating formerly manual procedures and enabling enhanced processes where humans and AI collaborate in a positive way (Wu et al., 2025). AI enables businesses to survive crises and hence must be utilized by businesses to build adaptive transformation and sense-and-respond capabilities that would spur innovation, enhance customer service and experience, and promote improved performance (Alghamdi & Agag, 2023).

In China, AI contenders on a giant scale which are extending AI use in important societal and economic sectors such as agriculture, transport, health, education, intelligent cities, manufacturing and finance include Tencent, Alibaba and Baidu. A new report by Centre for Data Innovation pointed out that China is the global leader in data and AI innovation. The

state council of China launched the New Generation Artificial Intelligence Development Plan (AIDP) in 2017 aimed at transforming the country into the global AI innovation center by 2030. The innovation system in China is complex, heterogeneous and large. Regions differ in terms of innovation modes and capabilities (Lundvall & Rikap, 2022).

German Pharmaceutical firms have seen increase in innovative products and services through technological advancements. Technology applications including web interactivity, internet of things, Chatbots, big data, and information systems have enabled entities to gain competitive advantage, expand business operations and expand customer reach. Within the Pharmaceutical industry, digital innovation has enabled development of electronic health records for patients, round the clock medical facilities access and virtual checkups. The self-tuning model relates to the capacity of the organization to adapt timely and efficiently towards market changes through learning, technological exploration, and exploitation (Cao & Leung, 2020). This consists of organization ambidexterity, adaptability and agility leading to the implementation of product innovation by organizations through smart manufacturing.

One of the determinants of innovative capacity is government. There are high levels of interventions by the Singaporean government in various areas in the society. However, Hong Kong on the other hand favors positive non-intervention policy that freezes the government influence power in the market and leans on free economy. Hong Kong has smaller R&D activities compared to Singapore where 10% of R&D activities were performed by government institutions, 29% universities and research institutes and 61% by industry. Universities and research institutes in Hong Kong accounted for 51% of R&D spending outperforming the industry which together with the government sector adding 45% and 4% in that order. Trade, accommodation and food service, and finance dominated Hong Kong's industry sector, accounting for 88% of R&D personnel in the industry and 89% of business R&D expenditure (Wang, 2018).

The government of South Korea is expanding R&D subsidies to improve national competitive advantages by strengthening firms' innovation competence. Korea's R&D expenditure accounts for US$78.856 bn, ranking fifth in the world, and its R&D to GDP ratio is 4.81%, which ranked a global second in 2020. Korea's R&D subsidy system has recently invested more in SMEs for their innovation activities. In addition, in 2020 the Korean government invested about US$151 million to promote collaboration between SMEs, universities, and research institutes and to support technology commercialization in SMEs located in an Innopolis (Son, 2025).

Telecommunication companies in Abuja, Nigeria, including Airtel and 9Mobile, face challenges and difficulties from a competitive context, poor data quality and strength, issues of data integration from different sources, a low adoption of business intelligence systems, and inconsistent competitors' data among mobile telecommunication companies. Specifically, the consistency, dynamism, and complexities of technological and economic variables were critical recent banes that cause the miss-shape and disintegration of competitive advantage among mobile telecommunication companies in Nigeria. The adoption of business intelligence has significantly enhanced the competitive advantage, sustainability, and profitability telecommunication companies. Business intelligence practices represent a strategic avenue that contemporary mobile telecommunications firms can employ to enhance their competitive strengths comprehensively (Mohammed & Sunday, 2024).

In Tanzania, there is emergence of big data analytics as a popular technology and banking is one of the industries viewed as an early adopted of IT data to drive making of decisions in an organisations. This due to the system's ability to store and process vast consumer data with its interactive channels. Several empirical findings about big data dwells on industrialized societies and hence though complex, their infrastructural growth and IT development do not match the status in developing countries. Tanzania is on the right step towards catching up

with other competitors with regards technology adoption. Research on technology adoption in the banking sector reveals differences between developing and developed countries due to differences in innovative advancements in banking technologies (Mwemezi & Mandari, 2024).

In Kenya, the emergence of big data tremendously transformed the financial business supporting data-driven decision making. This has led to the growth of Fintech. Businesses are using big data to analyze data for their clients from many sources including sites such as you tube, twitter, Instagram and Facebook to generate credit scores that are used to calculate how much to lend to a customer. BDA has also been used by many firms in improving service delivery. Thus, data is being generated at an ever-increasing rate. Kenya is going into the big data revolution, with the cooperation with huge multi-national firms with mutual interests and development of big data initiatives. However, there are a number of issues connected with big data including competition from existing businesses, lack of consumer confidence and data theft (Ogutu, 2024).

1.1.1 AI Business Models

Artificial intelligence (AI) has brought about transformation in the business environment by enabling firms to create innovative products, enhance decision-making and optimize processes (Wamba-Taguimdje et al., 2020). Entity performance has greatly been influenced by the adoption of AI business-based models since it has enabled firms to improve on decision-making, reduce costs and enhance efficiency. AI business-based models allow firms to access advanced AI capabilities without necessarily investing heavily hence improving flexibility and scalability (Khan et al., 2025). The models also allow firms integrate AI-driven analytics, machine learning and automation in their operations. The AI business-based models enhance the performance of firms by providing access to real-time business insights,

accelerating innovation as well as reducing infrastructure costs for better strategic planning (Aithal, 2023).

AI business-based models play a critical role in enhancing productivity of firms by streamlining business processes as well as minimizing manual work. The models also help the firms to increase efficiency, improve on response times and customer service as well as reduce labor costs thus leading to enhanced fir performance (Jorzik et al., 2024). AI business-based models also enable firms allocate resources to more value-added activities, reduce errors as well as enhance operational accuracy. The models enhance the performance of firms by improving customer satisfaction, accuracy and speed hence leading to better performance and competitive advantage of the firms (Aithal, 2023).

AI-driven data analysis helps the firms to optimize their strategies through predictive insights and hence enables businesses to enhance risk management, detect fraud and anticipate market trends (Boinapalli, 2023). The firms that utilize AI in making decisions resulting enhanced operational efficiency and better financial performance. Firms can make more informed decisions, reduce uncertainties, and optimize their marketing and supply chain operations, leading to greater business success (Badmus et al., 2024).

AI-enabled service and product innovation significantly enhances entity performance by creating new revenue sources and improving customer experiences. AI-driven recommendation systems, personalized marketing, and autonomous technologies allow firms to offer more tailored solutions, increasing customer engagement and retention (Kumar et al., 2023). Companies use AI to enhance user satisfaction, differentiate their offerings, and drive sales growth. Thus, by utilizing AI in product development and service delivery, firms can strengthen their market position, boost brand loyalty, and achieve long-term profitability in an increasingly AI-driven business environment (Rane et al., 2024). This study narrows down

to the effect of AI-based predictive fraud detection, risk management, portfolio optimization and financial modeling on performance of listed firms in Kenya.

AI-based portfolio optimization strategies can process huge, complex datasets in real-time, uncovering nuanced patterns and relationships that conventional statistical models often miss. AI-driven techniques continuously adapt to evolving market dynamics, assess non-linear risks and incorporate alternative data sources such as macroeconomic indicators (Kumari, 2024). AI-based risk management leverages machine learning algorithms, real-time analytics and big data to detect emerging risks and predict potential exposures with far greater precision. Traditional risk management often relies on static models, periodic reporting, and backward-looking metrics, which fail to adapt quickly to rapidly changing conditions (Li et al., 2024). AI-based fraud detection combines machine learning, pattern recognition and real-time data analysis to identify suspicious activities with higher speed and accuracy. Traditional approaches typically depend on manual reviews, which can struggle to detect novel fraud schemes and often generate high false-positive rates (Faisal et al., 2024).

1.1.2 Performance of Listed Firms in Kenya

The performance of listed firms in Kenya is influenced by various economic, regulatory, and market factors. The key performance indicators for the listed firms include return on investment, stock price trends, profitability and revenue growth. The performance of the listed firms in significantly influenced by interest rates, exchange rate fluctuations and inflation, as they influence consumer spending, production costs, and investment levels (Aayale et al., 2022).

Artificial intelligence in the financial industry is more about chat bots. AI in the banking sector brings about advanced data analytics power to bring about compliance by dealing with fraudulent transactions. AI is used by the banking sector in a very innovative way saving

money and time. The banks use algorithms to generate accurate results which in turn help in enhancing customer service and generate better sales performance to deliver profits (Kenya Bankers Association, 2022). NSE is using AI tools for data collection, enhance efficiency in gathering and analyzing ESG-related information providing a more comprehensive view of a company's sustainability performance (NSE, 2023).

A number of listed firms at NSE have recorded consistent profitability and growth of revenues including Equity group holdings and Safaricom PLC (Juma, 2022). Equity Group Holdings reported a pre-tax profit of Ksh. 51 bn for the first 3 quarters of 2024, an improvement from Ksh. 45.9 bn in the same period in 2023. Safaricom reported a 14% increase in group service revenue for the half year ending 2024 but a decline in net income by 17.7% following the depreciation of Ethiopia's birr (NSE, 2024). NSE lifted the suspension of the trading shares of Kenya Airways in 2025, following the improved performance as the carrier recorded Ksh. 10.53 bn in operating profits in 2023, its first operating profit since 2017 (NSE, 2024). These developments point out to improving performance of some of the listed firms reflecting strategic initiatives adopted by these firms to improve on their profitability.

The listed firms in the financial sector, particularly banking and insurance companies, plays a dominant role in Kenya's stock market. Firms including Cooperative Bank, KCB Bank and Equity Group have demonstrated strong performance due to digital banking innovations, increased financial inclusion, and regional expansion. However, challenges including non-performing loans (NPLs) and regulatory changes can affect profitability. The Central Bank of Kenya's monetary policies, including interest rate adjustments and lending regulations, also affect the financial health of these institutions (Alshebmi et al., 2020).

In the manufacturing and telecommunications sectors, firms like Safaricom and East African Breweries Limited (EABL) have consistently recorded impressive financial performance. The

manufacturing firms face challenges including high production costs, supply chain disruptions, and competition from imports. Government incentives, infrastructure investments, and trade policies play a crucial role in shaping the performance of these sectors (Kanike, 2023).

Despite growth opportunities, market volatility and external factors pose risks to the performance of Kenyan listed firms. Global economic trends, geopolitical issues, and commodity price fluctuations affect investor confidence and stock market stability (Kinyua & Fredrick, 2022). Furthermore, corporate governance, transparency, and sustainability initiatives are becoming increasingly important in attracting foreign and institutional investors. By leveraging on technology, innovation, and strategic partnerships, these firms are likely to experience sustained growth and enhanced shareholder value in dynamic business environment in Kenya (Gathara et al., 2019).

1.2 Statement of the Problem

Financial performance of listed firms is significant in increasing the value of firms and hence boosting the expansion across all the economic sectors accelerating the expansion of the country's economy. The key performance indicators for the listed firms include return on investment, stock price trends, profitability and revenue growth. A number of listed firms at NSE have recorded consistent profitability and growth of revenues including Equity group holdings and Safaricom PLC. Equity Group Holdings reported a pre-tax profit of Ksh. 51 bn for the first 3 quarters of 2024, an improvement from Ksh. 45.9 bn in the same period in 2023. Safaricom reported a 14% increase in group service revenue for the half year ending 2024 but a decline in net income by 17.7% following the depreciation of Ethiopia's birr. NSE lifted the suspension of the trading shares of Kenya Airways in 2025, following the improved performance as the carrier recorded Ksh. 10.53 bn in operating profits in 2023, its first operating profit since 2017. These developments point out to improving performance of some

of the listed firms reflecting strategic initiatives adopted by these firms to improve on their profitability.

However, although many firms are increasingly leveraging AI applications to improve forecasting accuracy, mitigate risks, enhance investment decisions and prevent fraudulent activities, there is limited empirical evidence on how such innovations translate into measurable financial results for the firms listed at NSE. It is against this that this investigation sought to establish the effect of AI-based business models on financial performance of listed firms in NSE.

A number of studies have been conducted by various scholars. However, research gaps were notable. A study was conducted by Wamba-Taguimdje et al. (2020) on the influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. The investigation presented conceptual and contextual gaps as it focused on AI-based transformation projects' business value whereas the investigation at hand focuses on AI-based business trading and firm performance. A study was carried out by Agarwall et al. (2022) on whether artificial intelligence influence the operational performance of companies. Secondary data collected from annual reports of entities under review was used. The investigation presented conceptual, methodological and contextual gaps as it focused on whether AI influence the operational performance using secondary data whereas the study at hand focuses on AI-based business trading and firm performance using primary data. A study was conducted by Dawson and Agbozo (2024) on AI in talent management in the digital era. Top modelling, computational literature and desk research was adopted in the study. Conceptual, methodological and contextual gaps were notable as it focused on AI in talent management in the digital era using top modelling, computational literature and desk research whereas the study at hand focuses on AI-based business human resource and management of talent and firm performance using a descriptive research design.

1.3 Research Objectives

In this study, a general and specific objectives directed this study.

1.3.1 General Objective

To determine the effect of AI-based business models on financial performance of listed firms in Nairobi Securities Exchange.

1.3.2 Specific Objectives

The following were the specific objectives to;

i. Determine the effect of AI-based predictive financial modelling on financial performance of listed firms in Nairobi Securities Exchange.

ii. Investigate the effect of AI-based risk management on financial performance of listed firms in Nairobi Securities Exchange.

iii. Examine the effect of AI-based portfolio optimization on financial performance of listed firms in Nairobi Securities Exchange.

iv. Determine the effect of AI-based fraud detection on financial performance of listed firms in Nairobi Securities Exchange.

1.4 Research Hypotheses

i. H_{01}: AI-based predictive financial modelling has no statistically significant effect on financial performance of listed firms in Nairobi Securities Exchange.

ii. H_{02}: AI-based risk management has no statistically significant effect on financial performance of listed firms in Nairobi Securities Exchange.

iii. H_{03}: AI-based portfolio optimization has no statistically significant effect on financial performance of listed firms in Nairobi Securities Exchange.

iv. H_{04}: AI-based fraud detection on financial performance of listed firms in Nairobi Securities Exchange.

1.5 Significance of the Study

The investigation would be significant to policy, practice and research. The outcomes would be significant to the companies listed at NSE as it would provide the benefits AI-supported business-based models on the performance of these firms. Specifically, the outcomes would be useful to the firms under study on the essence of AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection. The outcomes would be significant in how AI-supported business-based models in enhancing the performance of the firms under investigation.

The outcomes of the investigation would also be significant to the policy makers especially Nairobi Securities Exchange as well as other authorities on the importance of enacting policies that support the integration of AI in the business operations of the firms to enhance the performance of the firms. The outcomes would be significant for the authorities in formulating policies that support the adoption of AI-supported business-based models to enhance the performance of the firms under investigation.

The research outcomes would be helpful to scholars in the future who may want to utilize them as a foundation for additional research on this topic. The outcomes of the investigation would inform research gaps where future scholars would dwell on. The results would also inform the existing literature in AI-supported business-based models and performance of NSE listed entities.

1.6 Scope and Delimitation of the Study

This investigation explored the effect of AI-supported business-based models and financial performance of firms listed at NSE. There are several forms of AI-based business-based

models. However, the study specifically focused on AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection. The study also specifically focused on the firms listed at NSE within Nairobi County. Diffusion of innovation theory anchored the investigation. The unit of analysis for the study were firms listed at NSE whereas heads of marketing departments, business development department, human resource departments and operations department formed the unit of observation. There are several research philosophies and designs that can be used in research studies. However, the investigation used positivist research philosophy and correlational research design. The study also focused on financial listed firms because they operate in data-intensive environments where predictive modelling, risk management, portfolio optimization and fraud detection are critical to competitiveness and regulatory compliance.

1.7 Theoretical Framework

Diffusion of innovation theory anchored the research.

1.7.1 Diffusion of Innovation Theory

The theory was postulated by Rogers in 1962 and states that innovation is the spontaneous dispersion of ideas. The theory provides an understanding on the patterns, speed and how practices, products or ideas spread across the population. Thus, the theory attempts to illuminate how innovative ideas, concepts and technologies are developed and shared within (Rogers, 1962). According to the theory, innovation success relies on five virtues compatibility, relative advantage, simplicity, ease of use and results (Kaminski, 2011). Relative advantage defines the level at which a concept, idea or technological innovation is better than earlier innovations, ideas or technologies. The costs of innovation and social status form the critical aspects that define relative advantage of an innovation (Rogers, 2003). Compatibility defines how the innovation, idea or concept match with the existing technologies and systems or innovations to come in the future for smooth transition and

improvement (Peixoto, Castro & Nascimento, 2015). Ideas, technological innovations that are compatible with others are most preferred. On the other hand, complexity defines the level at which the innovation is hard to learn use and comprehend. Rogers (2003) argued that complexity of an innovation is negatively correlated with its level of use and adoption.

The theory is useful to the investigation because it explains the pattern and speed at which, ideas, practices and products are spread across population. The theory attempts to illustrate how concepts, ideas and technologies are developed and shared within. Hence, the theory explains how the adoption of AI-supported business-based models including AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection are significant in enhancing the financial performance of NSE listed firms.

1.8 Conceptual Framework

A conceptual framework depicts pictorial visualization of how thoughts, concepts or ideas are arranged to depict certain relationship among concepts or variables. The investigation embraced a conceptual framework that indicates relationship between independent variables (predictive financial modelling, risk management, portfolio optimization and fraud detection) and financial performance of listed firms (dependent variable) as indicated in Figure 1.1.

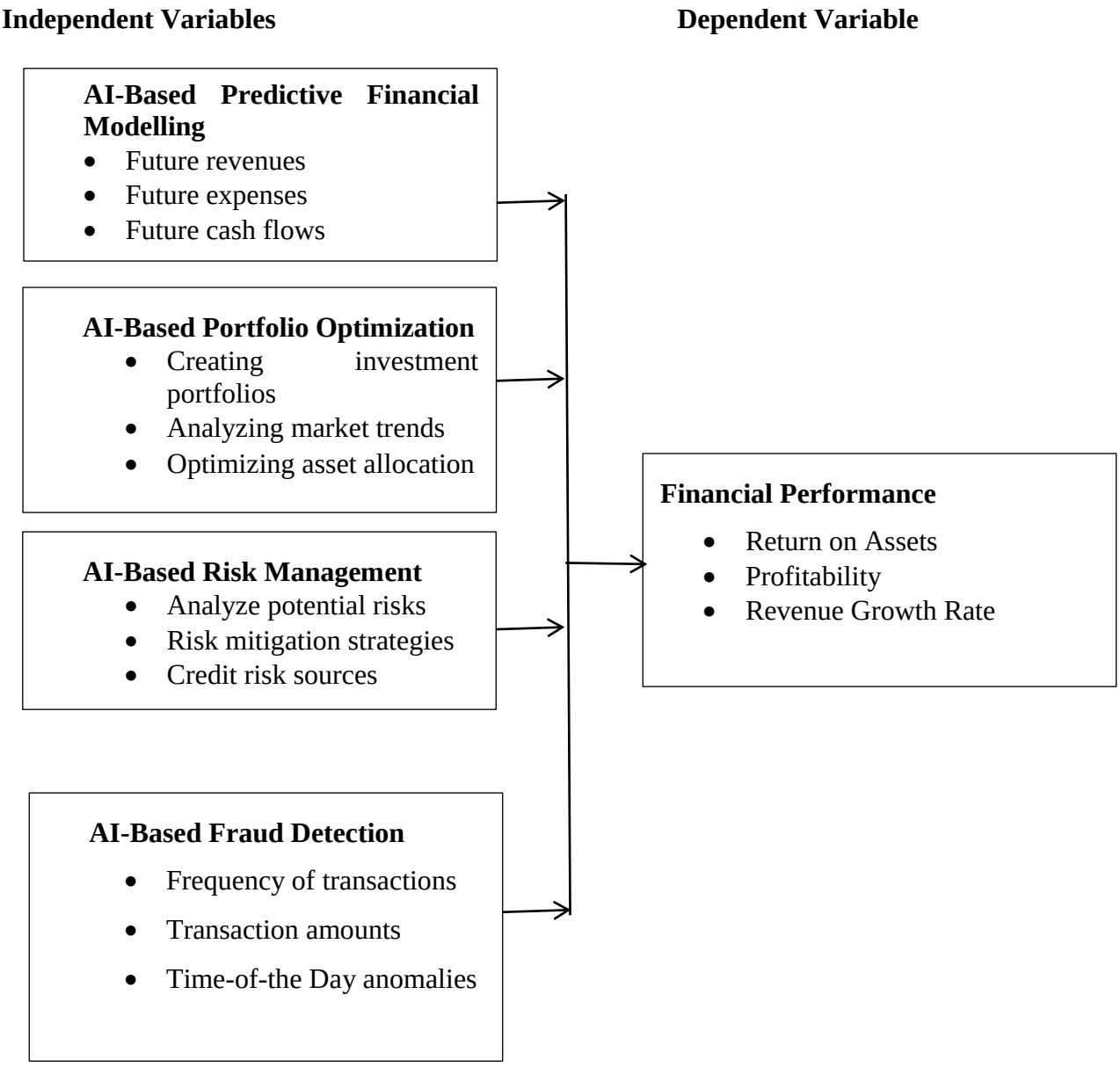


Figure 1.1: Conceptual Framework

Source: Researcher, 2025

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Chapter two outlines the review of literature reacting to the study objectives. It covers both empirical and theoretical literature. The theoretical literature entails the review of the theories anchoring the investigation. Empirical literature provides a foundation on findings of empirical studies on AI and organization performance.

2.2 Theoretical Foundation

The theories guiding the study include diffusion of innovation theory, Technology-Organization-Environment model and TAM.

2.2.1 Diffusion of Innovation Theory

The theory was postulated by Rogers in 1962 and states that innovation is the spontaneous dispersion of ideas. The theory provides an understanding on the patterns, speed and how practices, products or ideas spread across the population. Thus, the theory attempts to illuminate how innovative ideas, concepts and technologies are developed and shared within (Rogers, 1962). According to the theory, innovation success relies on five virtues compatibility, relative advantage, simplicity, ease of use and results (Kaminski, 2011). Relative advantage defines the level at which a concept, idea or technological innovation is better than earlier innovations, ideas or technologies. The costs of innovation and social status form the critical aspects that define relative advantage of an innovation (Rogers, 2003). Compatibility defines how the innovation, idea or concept match with the existing technologies and systems or innovations to come in the future for smooth transition and improvement (Peixoto, Castro & Nascimento, 2015). Ideas, technological innovations that are compatible with others are most preferred. On the other hand, complexity defines the level at

which the innovation is hard to learn use and comprehend. Rogers (2003) argued that complexity of an innovation is negatively correlated with its level of use and adoption.

The theory is significant because it explains the pattern and speed at which, ideas, practices and products are spread across population. The theory attempts to illustrate how concepts, ideas and technologies are developed and shared within. Hence, the theory explains how the adoption of AI-supported business-based models including AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection are significant in enhancing the performance of the firms listed at NSE.

DOI) theory is relevant to the study because it explains how organizations adopt and integrate new technologies such as AI, to gain competitive advantage and improve performance outcomes. By framing AI adoption through the DOI lens, the study can assess how factors like relative advantage, compatibility, complexity and organizational readiness influence the pace and success of AI-driven business model innovations in enhancing financial performance.

2.2.2 Technology-Organization-Environment Framework (TOE)

The theoretical framework was developed by Tornatzky and Fleischer (1990) providing the understanding on various factors influencing technological adoption and use such as the external environment under which the firm operates, the firm context in which technology is used as well as the characteristics of the technology itself. Thus, the framework is made up of three components including environment, organization and technology. Environment entails external context where the entity operates and covers factors such as cultural and social norms, regulatory requirements as well as the prevailing conditions in the market. Organization entails internal context such as resources, culture, structure as well as the size of the firm in which technology is used. Technology however refers to characteristics of the

technology itself including ease of use, compatibility with existing systems, complexity and functionality (Awa et al., 2017).

TOE framework does not solely focus on organizational context or technology itself but considers both external and internal factors as significant in shaping use and adoption of technology. Thus, the framework looks at a holistic perspective on implementation and adoption of technology which one of its strengths (Malik et al., 2021).

Another strength of the TOE framework is its flexibility (Al Hadwer et al., 2021). The framework is useful to practitioners and researchers in variety of fields as it can be used in a wide range of organizational contexts and technologies. Additionally, the framework can be adapted to different research methods, including qualitative and quantitative approaches (Baker, 2011).

One of the limitations of the framework is that it may be general and overly broad hence it may not be easy be used in specific situations. Furthermore, the framework may not fully capture the complexity of technology adoption and implementation, particularly in rapidly changing environments where external factors can have a significant impact on technology decisions (Awa et al., 2016).

The framework is of relevance to the study as it underlines the factors influencing technological adoption by listed firms including technological, organizational and environmental factors. These factors are also particularly important in explaining the adoption of AI-based models among listed firms at NSE considering the rapid penetration of advanced information technologies.

2.2.3 Technology Acceptance Theory

The model was introduced by Fred Davis in 1989 (Davis, 1989). The theory postulates the presence of two factors that are key determinants of the adoption or acceptance of any

particular computer system including whether the system is useful as well as its perceived easy usage. The theory is used to explain the behavior of an individual to accept a particular computer system. The model is an improvement of the theory of reasoned action, which incorporates attitudes of the individual with the two variables of technology acceptance that is perceived usefulness of the system and its perceived ease of use (Zaineldeen *et al.*, 2020).

Technology acceptance model combines different variables such as attitude towards behavior, actual system use, behavioral intention, perceived usefulness and how easy to use. The intention use or adopt a technology according to the model determines the real utilization of the system. The actual usage of the system by the individual is determined by the perceived usefulness as well as perceived ease of use (Granić & Marangunić, 2015).

The perceived importance of a system entails the extent of believe by the user that the system would enhance performance. The perceived importance or usefulness of technology is important in its adoption as it influences the users' willingness to be engaged by the government during the implementation (Kasyoka *et al.,* 2022). The attributes of the theory lie in the perceived usefulness, user satisfaction, its usability and how easy to use. The value of technology can only be tapped when one believes in its perceived usefulness and adopts in the provision of various services (Kamau, 2022). The theory however fails to recognize the organizational setting, generality and parsimony during the initial stages of designing the model (Katua, 2019).

Major weakness of the Technology Acceptance Model is that it is static and not dynamic to reflect changes in technologies, user desires and industry expectations. E-government services like e-commerce are subject to constant changes based on use expectation. As a result, the Technology Acceptance Model, may fail to accommodate this as it does not reflect changes technological progress. This weakness would be cured by diffusion innovation theory. The theory explains how the adoption of AI-supported business-based models

including AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection are significant in enhancing the performance of the entities listed at NSE.

2.3 Critique of the Theories

2.3.1 Technology Acceptance Model

The theory has faced criticism from a number of scholars. Ajibade (2018) indicated that the theory cannot practically be applicable or suitable to companies, many entities and firms including libraries having regulation and rules, but for utilization by individuals and technology adoption. Furthermore, there are inadequacies in the application of the model by the SMEs in information adoption. Other critics argue that the model is not designed to serve the interests of the business or the institution. However, the model is designed to suit individual purposes and hence cannot vividly explain the reasons for use and acceptance of technology in a business context (Ajibade, 2018).

Technology acceptance model has also been criticized as it incorporates criticism triviality, restricted foretelling and descriptive capability, heuristic contentious value and is short of any practical value. The model is deficient of structural and cost imperatives necessitating innovation adoption (Raji *et al.,* 2022). In addition, the subjective measures including interpersonal influence and behavioral intention are applied by the model. However, the behavioral underlines cannot be quantified in a reliable manner in any observed study because of the associated subjective elements that include personal attributes, values and norms (Malatji *et al.,* 2020).

Other critics postulate that regarding technological implementation; the model is deficient of its implications for management. Further research along technological innovation is discouraged by the model because of its exclusive utilization of survey methods (Lapointe & Rivard, 2005). There has been a situation of theoretical chaos because of the attempt by

scholars to expand the model to suit the dynamic nature of the technological environment (Benbasat & Barki, 2007). The model is further criticized as it fails to clear differentiate between actuality and intent thus negatively affecting the academic researches (Meerza, 2017)

2.3.2 Technology-Organization-Environment

One of the key limitations of TOE is its broad and vague categorization of influencing factors, often oversimplifying the complex adoption process. The framework further does not account for the interactions between technology, organization and environment which may present an incomplete understanding on these factors (Munasser, 2024). The framework does not also take into account other factors organizational culture, resistance to change and the attitudes of employees which may significantly affect technological adoption. The other limitation of the framework is that it has a limited adaptability to rapid technological advancements (van Hoorn, 2024).

2.3.3 Technology Acceptance Model

Criticisms have been raised against the theory by various scholars. Technology acceptance model has also been criticized as it incorporates criticism triviality, restricted foretelling and descriptive capability, heuristic contentious value and is short of any practical value. The model is deficient of structural and cost imperatives necessitating innovation adoption (Raji *et al.,* 2022). In addition, the subjective measures including interpersonal influence and behavioral intention are applied by the model. However, the behavioral underlines cannot be quantified in a reliable manner in any observed study because of the associated subjective elements that include personal attributes, values and norms (Malatji *et al.,* 2020).

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utilization by individuals and technology adoption. There are inadequacies in the application of the model by the SMEs in information adoption. Other critics argue that the model is not designed to serve the interests of the business or the institution. However, the model is designed to suit individual purposes and hence cannot vividly explain the reasons for use and acceptance of technology in a business context (Ajibade, 2018).

2.4 Empirical Review

The empirical review involves the review of the existing literature on studies previously done but related to the topic of investigation. The review is instrumental in identifying the existing research gaps where more research is necessary. Thus, the review of literature is key as it would inform research gaps that informs the current investigation. The review of literature has been covered as per the objectives of the study.

2.4.1 AI-Based Predictive Financial Modelling and Financial Performance

Kang and Park (2021) researched on AI-based detection and predicting management of corporate earnings. The outcomes pointed out that over the last decade, there have been substantial increase in the adoption AI applications including machine learning attributed to the advancements in computer volume and growth of data volume. The adoption of these technologies enhances the accuracy of the model compared to conventional linear regression models. The investigation presented a conceptual gap as the current investigation sought to establish the effect of AI-based predictive financial modelling on financial performance of Kenyan listed firms.

A study was conducted by Wamba-Taguimdje et al. (2020) on the influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. IT capabilities theory was used. The results indicated that a range of technologies are covered by AI such as machine translations, self-learning algorithms and chatbots which

allow individuals to comprehend and act accordingly in their environments. The adoption of AI technological innovations by firms is aimed at enhancing their competitive advantage and further developing and optimizing strategic advantages. AI serves to improve automation, transformation and information and optimize existing processes. Contextual and conceptual gaps were presented as it focused on value of transformation projects that are AI-based whereas the study at hand focuses on AI-based predictive financial modelling and firm performance.

A study was conducted by Ho et al. (2022) on artificial intelligence and firm performance and whether machine intelligence shield firms from risks. Panel data were used in four periods. From the outcomes, the negative impact of Covid-19 was more severe on conventional stock markets in the immediate periods of the pandemic than on AI-stock market later. However, when financial market was exposed to the uncertainties of the pandemic, conventional stocks were less resilient. AI deployment is a crucial driver of sustainable performance in environments characterized by challenges. Conceptual and contextual gaps were observed as it focused on whether machine intelligence protect entities from risks whereas the study at hand focuses on AI-based predictive financial modelling and firm performance.

Shiyyab et al. (2023) on the impact of artificial intelligence disclosure on financial performance. Content analysis was used in the investigation and the results indicated that AI positively affects accounting performance and its effect on total expenses was negative. The performance of banks is affected by AI related keywords and disclosures though for AI related disclosures, it was weak for some banks. Contextual and conceptual gaps were noted as it focused on impact of AI disclosure on performance whereas the study at hand focuses on AI-based predictive financial modelling and firm performance.

A study was carried out by Agarwall et al. (2022) on whether artificial intelligence influence the operational performance of companies. Secondary data exacted from published reports of

the entities under review was used. From the results, AI significantly influences operating profit and cost of the companies under investigation. The investigation presented contextual and conceptual gaps as it focused on whether AI affects the operational performance whereas the investigation at hand focuses on AI-based predictive financial modelling and firm performance.

2.4.2 AI-Based Portfolio Optimization and Financial Performance

A study was conducted by Abrokwa-Larbi and Awuku-Labi (2024) with a focus on AI in marketing and SME's performance in an emerging economy using structural equation modelling. The outcomes postulated that in marketing, AI significantly impacts learning and growth, internal business process and financial performance with regards Ghanaian SMEs. Contextual and conceptual gaps were recorded as it focused on whether AI influence the operational performance whereas the study at hand focuses on AI-based portfolio optimization and firm performance.

Al-Sumi et al. (2022) researched on AI based decision making that is improving operational performance through combination of strategies. Structural equation modelling was used and the outcomes pointed out that firm structure moderates the mediation of strategy of marketing on performance while marketing strategy positively mediates on IT strategy and performance. The use of novel three-phase decision-making framework enhances decision accuracy, increases insights and improves operational efficiency at strategic levels in industries. Contextual and conceptual gaps were observed as it focused on combining strategies to enhance operational performance whereas the study at hand focuses on AI-based portfolio optimization and firm performance.

A study was conducted by Liu et al. (2024) on the impact of artificial intelligence capabilities on objective firm performance. The study pointed out that entities are continuously increasing

investments to boost efficiency, lower costs and boost revenues. The results of the investigation were however mixed regarding AI project adoption. Conceptual and contextual gaps were noted as it focused on the impact of AI capabilities whereas the investigation at hand focuses on AI-based portfolio optimization and firm performance.

Caner (2024) evaluated on the effect of artificial intelligence on perceived business performance of Turkish firms in technology development zones in Türkiye which are generally more technology-oriented. From the outcomes, there was a positively significant correlation between perceived business performance and implementation of AI. The investigation concluded that the adoption of AI could be significant in improving performance of businesses, however, with regards TDZs in Turkiye, its effect is modest. Contextual and conceptual gaps were attracted as it focused on AI and perceived business performance of Turkish entities whereas the study at hand focuses on AI-based portfolio optimization and firm performance in Kenya.

A research study was conducted by Chen et al. (2023) on firm AI adoption intensity and marketing performance. The results indicated that normative pressure, the support from top management and technological opportunism are the primary drivers behind AI adoption intensity. Increasing intensity in AI adoption improves the marketing performance of entities significantly as it enhances the capabilities to adapt to the ever changing and dynamic businesses environment. The investigation presented conceptual and contextual gaps as it focused on AI adoption intensity and marketing performance whereas the study at hand focuses on AI-based portfolio optimization and firm performance.

2.4.3 AI-Based Risk Management and Financial Performance

Li et al. (2024) researched on how stock price cash risk is affected by AI in emerging market using ordinary least squares. The results indicate that adoption of AI significantly reduces the

likelihood of risk of stock price crash. The adoption of AI contributes to reduction in firm SPCR as it enhances the quality of internal control. This association is more strong among non-SOEs in comparison to SOEs. The investigation presented conceptual and contextual gaps as it focused on influence of AI on SPCR in emerging market whereas the study at hand focuses on AI-based risk management and firm performance.

Faqihi and Miah (2023) studied on artificial intelligence-driven talent management system: Exploring the risks and options for constructing a theoretical foundation. Data science research was used in the study. The key goal of the initiative is improving connections between planning features and professional assessments. The functionalities of AI can be significant in assisting professional talent managers by investigating, predicting and identifying talent management and trends related to performance. AI can be resourceful in developing chatbots which frequently answers questions on resumes, job applications and careers. Conceptual, methodological and contextual gaps were recorded as it focused on AI-driven talent management system using data science research whereas the study at hand focuses on AI-based risk management and firm performance using a descriptive research design.

A study was conducted by Saffari (2024) on ranking of business risks by artificial intelligence and multi-criteria decision making. The study discussed limitations of traditional risk management methods. The outcomes indicated that the integration of AI and MCDM provides a promising approach for enhancing the effectiveness of business risk management. By leveraging AI's data-driven analysis and predictive capabilities alongside the structured decision-making framework of MCDM, organizations can comprehend the evolving risk landscape and make more informed strategic decisions. Contextual and conceptual gaps were noted as the investigation at hand focuses on AI-based risk management and firm performance.

Paul et al. (2021) studied on the adoption of artificial intelligence in supply chain risk management: an Indian perspective. Data was conducted from AI consultants, risk professionals and supply chain executives across transportation, retail trade, wholesale trade and manufacturing in India. From the outcomes, the factors under review recorded varying degrees of impact on adoption of AI in SCRM. Conceptual and contextual gaps were presented as it focused on adoption of AI in Indian SCRM whereas the study at hand focuses on AI-based risk management and firm performance.

A study was carried out by Kanti et al. (2022) on artificial intelligence adoption in supply chain risk management: Scale development and validation. Surveys were collected across various industries in India. The adoption of AI is necessary considering emergence of pandemic led disruptions from global and local supply chains and operations. The investigation presented conceptual and contextual gaps as it was conducted in SCRM in India whereas this study at hand focuses on AI-based risk management and firm performance with focus to financial firms.

2.4.4 AI-Based Fraud Detection and Financial Performance

A study was conducted by Narsina et al. (2019) on AI-driven database systems in fintech: enhancing fraud detection and transaction efficiency. The study synthesized existing literature and industry reports to assess financial services AI integration performance via secondary data evaluation. From the results, AI improves fraud detection by identifying complex patterns, reacting to new risks, and increasing transaction efficiency via automation, intelligent routing, and real-time optimization. These innovations speed up transaction processing, save operating expenses, and minimize fraud losses. The investigation however presented conceptual and methodological gaps as the current investigation relied on primary data to assess the effect of AI-based detection of fraud and financial performance of listed Kenyan organizations.

Hussain et al. (2025) further studied on examining the role of ai in detecting fraudulent activities, managing financial risks and enhancing decision-making in investment strategies. This was a quantitative study used primary data. From the results, there was a positive association between AI tools implementation for detection of fraud, enhanced decision abilities and risk management in overall. There was improvement in timeliness and accuracy to fulfill the regulatory compliance needs. The investigation however presented conceptual gap as the current investigation assessed the effect of AI-based fraud detection and performance of Kenyan listed firms.

A study was conducted by Mohammed and Rahman (2024) on the role of artificial intelligence (AI) on the fraud detection in the private sector in Saudi Arabia. Both qualitative and quantitative approaches were used. The results indicated that by incorporating data analytics, machine learning algorithms, and AI models, firms can identify and mitigate fraudulent activities effectively and hence protecting reputation and financial assets. Conceptual and methodological gaps were presented as the current investigation relied on quantitative data only to assess the effect of AI-based detection of fraud and performance of listed Kenyan entities.

Yuhertiana and Amin (2024) conducted a systematic literature review on Artificial Intelligence driven approaches for financial fraud detection. The findings demonstrated that adoption of AI techniques of fraud detection have proven effective and precise in identification of fraud pattern. Conceptual and methodological gaps were noted as the current investigation relied on primary data only to assess the effect of AI-based detection of fraud and performance of listed entities in Kenya.

A study was conducted by Aljunaid et al. (2025) on secure and transparent banking; explainable AI-driven federated learning model for financial fraud detection. The study indicated that while AI improves the detection of fraud, its nature makes it hard for users to

refine, validate and trust decisions posing challenges for adversarial defense and fraud explanation. Federated learning ensures legal compliance, preserves data privacy and enables distributed training for detection of fraud. A conceptual gap was observed as the current investigation assessed the effect of AI-based fraud detection and performance of listed Kenyan firms.

2.5 Knowledge Gap

Kang and Park (2021) researched on AI-based detection and prediction of management of corporate earnings. A conceptual gap was evident as the current investigation seeks to determine the effect of AI-based predictive financial modelling on performance of listed Kenyan organizations. A study was conducted by Wamba-Taguimdje et al. (2020) on the influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. The investigation presented conceptual and contextual gaps as it focused on AI-based transformation projects' business value whereas the investigation at hand focuses on AI-based business trading and firm performance. Li et al. (2024) researched on tech for stronger financial market performance: the impact of AI on SPCR in emerging market. The investigation presented conceptual and contextual gaps as it focused on effect of AI on SPCR in emerging market whereas the study at hand focuses on AI-based business trading and firm performance. A study was conducted by Ho et al. (2022) on artificial intelligence and firm performance and whether machine intelligence shield firms from risks. Conceptual and contextual gaps were noted as it dwelled on whether machine intelligence protect entities from risks whereas the study at hand focuses on AI-based business trading and firm performance.

Shiyyab et al. (2023) on the impact of artificial intelligence disclosure on financial performance. The investigation presented conceptual and contextual gaps as it focused on impact of AI disclosure on performance financially whereas the investigation at hand focuses

on AI-based business trading and firm performance. A study was carried out by Agarwall et al. (2022) on whether artificial intelligence influence the operational performance of companies. Secondary data collected from annual reports of entities under review was used. The investigation presented conceptual, methodological and contextual gaps as it focused on whether AI influence the operational performance using secondary data whereas the study at hand focuses on AI-based business trading and firm performance using primary data.

A study was conducted by Abrokwa-Larbi and Awuku-Labi (2024) with a focus on AI in marketing and SME's performance in an emerging economy using structural equation modelling. Contextual and conceptual research gaps were observed as it focused on whether AI influence the operational performance in Ghana whereas the study at hand focuses on AI-based business marketing and firm performance in Kenya. Al-Sumi et al. (2022) researched on AI based decision making that is improving operational performance through combination of strategies The investigation presented conceptual and contextual gaps as it majored on improving operational performance by combining strategies whereas the study at hand focuses on AI-based business marketing and firm performance. A study was conducted by Liu et al. (2024) on the impact of artificial intelligence capabilities on objective firm performance. Conceptual and contextual gaps were notable as it dwelled on the impact of AI capabilities whereas the study at hand focuses on AI-based business marketing and firm performance.

Caner (2024) evaluated on the effect of artificial intelligence on perceived business performance of Turkish firms in technology development zones in Türkiye which are generally more technology-oriented. The investigation presented contextual and conceptual gaps as it dwelled on AI and perceived business performance of Turkish entities whereas the study at hand focuses on AI-based business marketing and firm performance in Kenya. A research study was conducted by Chen et al. (2023) on firm AI adoption intensity and

marketing performance. Conceptual and contextual gaps were observed as it focused on intensity of AI adoption and marketing performance whereas the study at hand focuses on AI-based business marketing and firm performance.

A study was conducted by Dawson and Agbozo (2024) on AI in talent management in the digital era. Top modelling, computational literature and desk research was adopted in the study. Conceptual, methodological and contextual gaps were notable as it focused on AI in talent management in the digital era using top modelling, computational literature and desk research whereas the study at hand focuses on AI-based business human resource and management of talent and firm performance using a descriptive research design. Faqihi and Miah (2023) studied on artificial intelligence-driven talent management system: Exploring the risks and options for constructing a theoretical foundation. Data science research was used in the study. The investigation presented conceptual, methodological and contextual gaps as it focused on AI-driven talent management system using data science research whereas the study at hand focuses on AI-based business human resource and talent management and firm performance using a descriptive research design.

A study was conducted by Saffari (2024) on ranking of business risks by artificial intelligence and multi-criteria decision making. Conceptual and contextual gaps were noted as the investigation at hand focuses on AI-based risk management and firm performance. Paul et al. (2021) studied on the adoption of artificial intelligence in supply chain risk management: an Indian perspective. Conceptual and contextual gaps were evident as it focused on adoption of AI in SCRM in India whereas the study at hand focuses on AI-based risk management and firm performance. A study by Kanti et al. (2022) on artificial intelligence adoption in supply chain risk management: Scale development and validation presented conceptual and contextual gaps as it was conducted in SCRM in India whereas the study at hand focuses on AI-based risk management and firm performance.

A study conducted by Narsina et al. (2019) on AI-driven database systems in fintech: enhancing fraud detection and transaction efficiency. The study synthesized existing literature and industry reports to assess financial services AI integration performance via secondary data evaluation. Conceptual and methodological gaps were notable as the current investigation relied on primary data to assess the effect of AI-based detection of fraud and financial performance of listed entities in Kenya. Hussain et al. (2025) further studied on examining the role of ai in detecting fraudulent activities, managing financial risks, and enhancing decision-making in investment strategies presenting a conceptual gap as the current study assessed the effect of AI-based fraud detection and financial performance of listed firms in Kenya. A study by Mohammed and Rahman (2024) on the role of artificial intelligence (AI) on the fraud detection in the private sector in Saudi Arabia. Quantitative and qualitative methods were used. Methodological and conceptual gaps were evident as the current study relied on quantitative data only to assess the effect of AI-based detection of fraud and performance of listed Kenyan entities.

Yuhertiana and Amin (2024) conducted a systematic literature review on Artificial Intelligence driven approaches for financial fraud detection. Conceptual and methodological gaps were noted as the current study relied on primary data only to assess the effect of AI-based detection of fraud and performance of listed firms. A study was conducted by Aljunaid et al. (2025) on secure and transparent banking; explainable ai-driven federated learning model for financial fraud detection. The investigation however presented conceptual gap as the current investigation assessed the effect of AI-based fraud detection and performance of listed Kenya entities.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.0 Introduction

Research methodology that the investigation used is presented in the chapter. This includes the data collection procedures, sample and sampling designs, research instruments, the target population and research design. In addition, the procedures of data analysis as well as diagnostic tests carried out and ethical considerations are also presented.

3.1 Research Philosophy

This refers a belief about a way of collecting, analyzing and using data about a phenomenon. It guides scientific discoveries through principles and assumptions (Shirima, 2020). Comprehending the specific assumptions of a paradigm is significant in enhancing the quality of findings that support scientific research studies and identifying relevant evidence. A positivist research philosophy was used in the study. The philosophy emphasizes objective, empirical observation and the use of scientific methods to uncover universal laws and truths. It assumes that reality is stable, measurable, and independent of subjective interpretation, prioritizing quantifiable data and logical reasoning in research. The philosophy was relevant in determining the relationship between AI-based business models and performance of entities listed at NSE.

3.2 Research Design

This refers to a plan that the researcher intends to adopt while conducting the research. It outlines the framework of methods and techniques that have been adopted by the researcher in answering the research questions in a manner that is logical. Thus, it entails a plan that directs the overall research procedure (Salter, 2023). The study used a correlational research design as the investigation seeks to determine the associations between AI-based business models and performance of listed entities in NSE. This type of research design is suitable in

gathering information on the conditions that prevail with the intention of interpretation and description. Correlational research design describes a situation or a phenomenon accurately by determining the relationships between variables.

3.3 Target Population

A target population in a research study involves the population of interest or the entire population or a set that possess the features that are of interest to the researcher and hence are considered to be essential for data analysis (Willie, 2022). The unit of analysis for the study were financial firms listed at NSE while the unit of observation were the heads of marketing departments, business development department, human resource departments and operations department within the 17 financial firms listed at NSE (Nairobi Securities Exchange, 2025).

Table 3.1: Target Population

Department	**Number of Respondents**	**Target Population**
Marketing	1	17
Business Development	1	17
Human Resource	1	17
Operations	1	17
Total	**4**	**68**

Source: Researcher, 2025

3.4 Sample and Sampling Techniques

A sample entails selected objects or persons who are to take part in a study and represents a subset of a population. A sample is representative of the whole target population. Hence, the process whereby a sample is selected from the target population entails a sample (Etikan & Bala, 2017). Since the target population of the investigation is relatively small, the investigation conducted a census of all the respondents.

3.5 Research Instruments

The investigation utilized both primary and secondary information. Primary data provides field data from the investigation unit observation and thus was provide useful in studying AI-

based business models and financial performance of listed entities. A structured questionnaire was adapted in collecting primary data. A questionnaire contains a set of structured questions that are meant to collect the data that is meaningful to the study (Burns & Burns, 2008). The key advantages of using a questionnaire lies in its easy construction, portability as well as its ability to be used for large data sets and its analysis can be easy. The closed ended questions were presented in a Likert scale and was structured into various sections where the first contained questions pertaining respondents' demographic information. Section B, C, D and E contained questions on the independent variables while section F covered questions on the dependent variable. Secondary data was conducted for the dependent variable (financial performance) using the secondary data collection template attached in the appendices.

3.6 Pilot Study

This represents a pilot study that is conducted by the researcher to test reliability and validity of the tool. The study contacted 10% of the sample size to participate in the pilot study (Kennedy et al., 2011). Before the actual data collection exercise is conducted, the researcher conducted a pre-study purposely to measure reliability and validity of the instrument to be used in data collection. Thus, the researcher contacted 7 respondents from the departments including marketing departments, business development department, human resource departments and operations department within the firms listed at NSE. The participants who were involved in the pilot test were not included in the main investigation. The results of the pilot test were of importance in improving the questionnaire.

3.6.1 Test for Reliability

The reliability test is significant because the results determines whether the data collection instrument is able to gather data, that when analyzed can give meaning and reliable conclusions (Joppe, 2010). Thus, carrying out the test is essential before the actual data collection exercise is conducted. Cronbach's Alpha method was used and as a decision rule,

values > 0.7 implied the reliability of the data collection while values<0.7 would imply the need for improvement of the data collection instrument.

3.6.2 Test for Validity

The test for validity is used in assessing whether the questionnaire can adequately measure what it is intended to measure of if the data collection instrument can adequately achieve the objective of the study (Joppe, 2010). Construct and content validity was measured in the investigation. For content validity, the input of the supervisor and other experts was sought to improve the contents of the data collection instrument. For construct validity, the researcher conducted Kaiser–Meyer–Olkin (KMO) tests. The variables with factor loadings >0.7 are allowed. However, other scholars have also allowed factor loadings >0.5 (Cooper and Schindler (2011). Similarly, Kılıç and Doğan (2021), argued that factor loading of 0.5 and above is acceptable.

3.7 Data Collection Procedures

Before collecting data, permissions were sought from CUEA University, National Commission for Science, Technology and Innovation (NACOSTI) and the respective listed to carry out data collection. Based on the pilot results, the questionnaire as improved prior actual data. The principal investigator recruited two research assistants who helped in administration and collection of the questionnaires who were trained on the research ethics before the data collection exercise. Drop and pick later method of administering the questionnaires were used to allow the respondents adequate time to provide the responses. The method is suitable so that the working schedules of the respondents are not disrupted and further to give the respondents ample time to fill the them and share their thoughts sufficiently. Once the questionnaires are received back, the data was cleaned and data entry done in an Excel spreadsheet before being uploaded to an SPSS software version 27 ready for analysis and presentation.

3.8 Data Analysis Procedures

Analysis of data was conducted using SPSS software and the results presented as descriptive and inferential outcomes in form of tables and charts. Pearson correlation test was undertaken to explore the direction and strength of association between the factors in the investigation. Multiple regression analysis was conducted to determine the influence of AI-based predictive financial modelling, AI-based risk management, AI-based portfolio optimization and AI-based fraud detection on financial performance of listed firms in the Nairobi Securities Exchange (Jeon, 2015). The model that was estimated was;

$$Y = \beta_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + X_4\beta_4 + \varepsilon$$

Where,

Y is financial performance of firms listed at NSE, β_0, β_1, β_2, β_3 and β_4 are constant terms, X_1 stands for AI-based predictive financial modelling, X_2 represents AI-based risk management, X_3 represents AI-based portfolio optimization and X_4 represents AI-based fraud detection. e represented the error term.

The overall model significance was ascertained checked using ANOVA. A significance value of 0.05 as well as the calculated F value was used. The critical F value and the estimated F value were compared. Furthermore, a critical p value of 0.05 was used to explore the significance of the individual regression coefficients.

3.9 Diagnostic Tests and Assumptions of the Multiple Linear Regression Model

Diagnostic tests were conducted to explore if the data collected is suitable to perform other analysis such as regression analysis, which is critical in meeting the objectives of the research. Failure to conduct assumptions of classical linear regression model and diagnostic tests may result to inaccurate parameter estimates of the model. The tests that were conducted include multicollinearity tests, normality tests and the tests for heteroscedasticity.

3.9.1 Multicollinearity

Multicollinearity represents a condition where two or more predictor variables are found to be highly linearly related (Montgomery *et al.*, 2015). One of the variables ought to be eliminated in the study, if two or more variables are correlated highly, as the two variables offer the same explanation. The study used Variance Inflation Factor (VIF) to measure multicollinearity (Alin,2010). As a decision role, VIF value>0.5 would signal the presence of multicollinearity whereas VIF values <0.5 would absence of multicollinearity. In cases where there is severe multicollinearity among two or more independent variables, one variable is retained in the study.

3.9.2 Normality

Normality tests are carried out to ascertain the consistency in the distribution of data (Yazici & Yolacan, 2007). To carry out single or joint hypothesis tests of the model, the normality assumption should be in place (Brooks & Condori, 2018). Normality tests were conducted using Shapiro-Wilk because the population for the study was small. A computed p-values >0.05 would imply that the data set collected follows normal distribution and hence fit for further analysis (Mishra *et al.*, 2019). To cure non-normality in data, apply transformations such as logarithmic to stabilize variance and make the data more closely resemble a normal distribution.

3.9.3 Heteroscedasticity

Heteroscedasticity is defined by Carapeto and Holt (2003) as a condition where the variability of a variable is unequal across a range of values of the predicting variable. The test was conducted to ascertain if certain data sets' observations are modified or same or if the error term of a particular variable under review is non-constant. The tests for heteroscedasticity was carried out employing Wooldridge tests. With this method, large Chi2

values would imply the presence of heteroscedasticity (Rosopa *et al.*, 2013). To address heteroscedasticity, apply data transformations like logarithmic to stabilize variance across the data.

3.10 Ethical Considerations

Before to the actual data collection exercise, permission was sought from the University, NACOSTI as well as the entities listed at NSE. The researcher also ensured that all the participants in the study are fully and adequately informed of the reason of conducting the investigation and the anonymity and confidentiality of the information that they provided. Furthermore, official dress code was maintained throughout the period of study, and that official language was adhered at all times while addressing and conversing with the respondents. The dignity of the respondents were also respected at all times. Two research assistants were contracted and adequately trained on the best ethical standards before being deployed to help in distribution and collection of the questionnaires. The professionalism of the researcher was upheld at all times during the study. The questionnaire did not provide any section for the names or particulars of any respondent. The entire source used in the study was acknowledged and referenced.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.0 Introduction

The chapter outlines the analysis of data and further presents the discussion of the results from the analysis. Primary data was used in the study. The data was analyzed using SPSS software and the outcomes presented in the form of inferential and descriptive outcomes. Descriptive results included percentages, frequencies, standard deviation and mean. Inferential outcomes included correlation and regression analysis statistics.

4.1 Response Rate

The study conducted a census of 68 respondents. Therefore, 68 structured questionnaires were distributed. Nonetheless, 54 questionnaires properly filed indicating a 79.4% response rate. Fincham (2008) points out that a response rate of approximately 60 percent is sufficient for a research study. Thus, the study response rate is sufficient for the study.

Table 4.1: Response Rate

	Frequency	**Percent**
Response	54	79.4
Non-Response	14	20.6
Total	**68**	**100**

Source: Researcher, 2025

4.2 Demographic Statistics

The demographic analysis of the study included the analysis on department, level of adoption of AI-Based business models, length of service and the importance of AI-Based business models.

4.2.1 Department

The investigation sought to determine the department in which the participants were working in and the results are shown in Table 4.2.

Table 4.2: Department of the Respondents

	Frequency	Percent
Marketing	19	35.2
Business Development	12	22.2
Human Resource	15	27.8
Operations	8	14.8
Total	**54**	**100**

Source: Researcher, 2025

From the results, 35.2 percent of the participants were based in the marketing department, 22.2 percent business development department, 27.8 percent under human resource department and 14.8 percent under the operations department.

4.2.2 Level of Adoption of AI-Based Business Models

The investigation sought to determine the level of adoption of AI-Based Business Models and the results are presented in Figure 4.1.

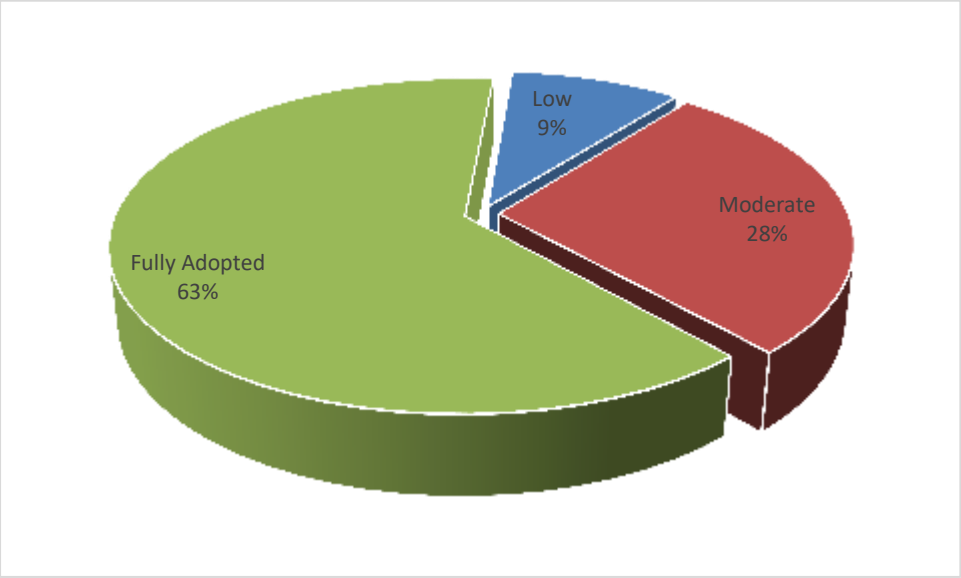


Figure 4.1: Level of Adoption of AI-Based Business Models

From the outcomes, 63 percent of the respondents indicated that AI-Business models had fully been adopted in their department, 28 percent moderately adopted and 9 percent indicated that the level of adoption was low.

4.2.3 Length of Service

The investigation sought to determine the length of service at the firm and the results are presented in Figure 4.2.

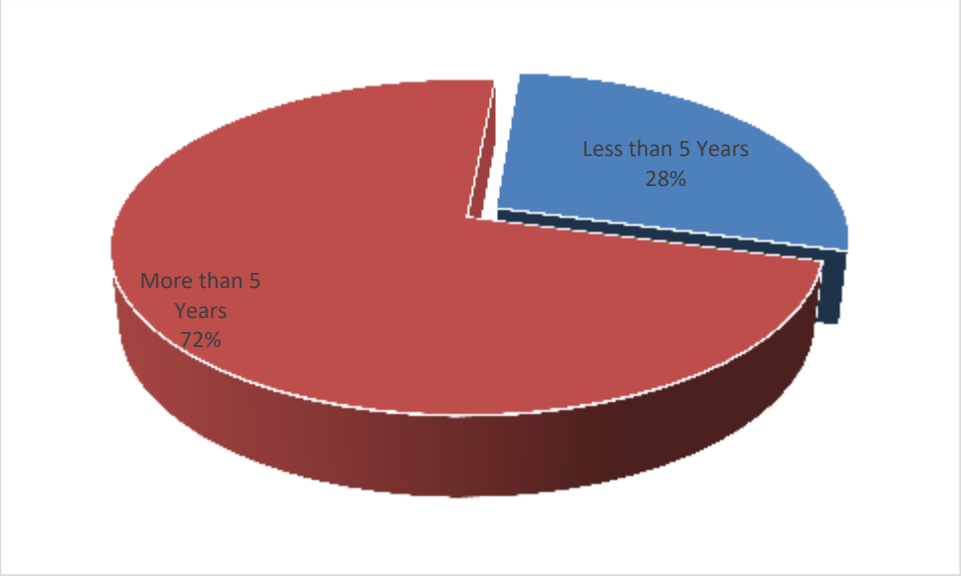


Figure 4.2: Length of Service

From the results, 72 percent of the participants had been working at their respective listed firms for more than 5 years while 28 percent indicated less than 5 years.

4.2.4 Importance of AI-Based Business Models

The study finally sought to determine whether AI-Based Business Models are important and the results are presented in Figure 4.3.

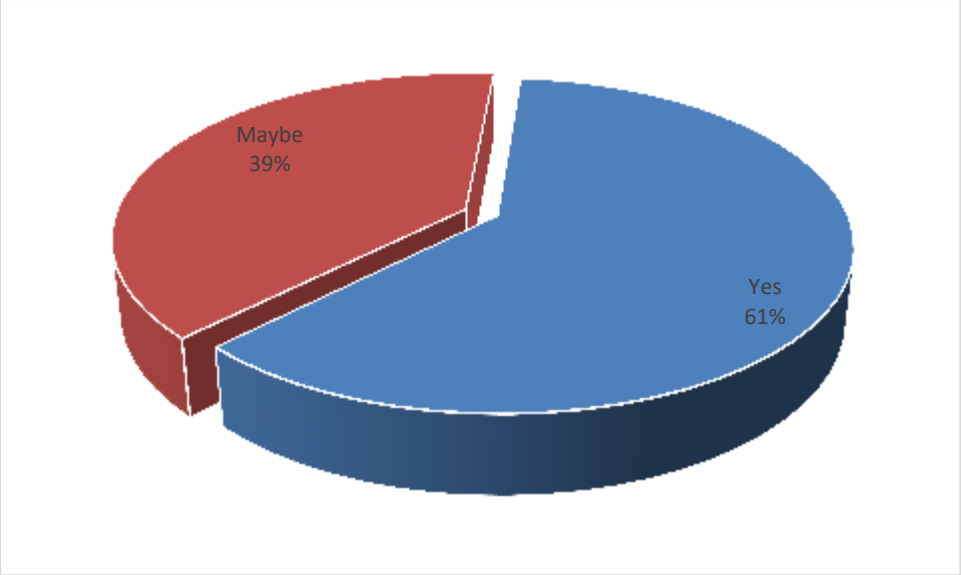


Figure 4.3: Importance of AI-Based Business Models

From the results, 61 percent of the respondents pointed out that AI-Based business models were important while 39 percent were not sure.

4.3 Descriptive Statistics

Primary data was utilized in the investigation. The data collected sing questionnaire was analyzed. The responses were measured on a Likert scale of 1-5 where; 5 represents strongly agree, 4 agree, 3 neutral, 2 disagree and 1 strongly disagree.

4.3.1 Descriptive Results for AI-Based Predictive Financial Modelling

A summarized table outlining the descriptive outcomes of the questions on AI-Based Predictive Financial Modelling is presented in the subsequent sections. The outcomes are shown in table 4.3.

Table 4.3: Descriptive Results for AI-Based Predictive Financial Modelling

	SD N %	D N %	N N %	A N %	SA N %	M	S Dev
AI-based predictive financial modelling forecasts future financial outcomes with greater accuracy	6 11.1%	4 7.4%	8 14.8%	18 33.3%	18 33.3%	3.7	1.3
Firms using AI in financial modelling can identify profitability trends	4 7.4%	5 9.3%	5 9.3%	24 44.4%	16 29.6%	3.8	1.2
Integrating AI into financial forecasting enhances the precision of cash flow projections	3 5.6%	5 9.3%	8 14.8%	24 44.4%	14 25.9%	3.8	1.1
The use of AI in financial modelling supports more informed investment decisions	7 13%	3 5.6%	4 7.4%	26 48.1%	14 25.9%	3.7	1.3
AI models can incorporate a wide range of data including macroeconomic indicators to produce holistic performance forecasts	4 7.4%	4 7.4%	2 3.7%	23 42.6%	21 38.9%	4.0	1.2
Predictive analytics powered by AI enables early detection of financial distress	2 3.7%	4 7.4%	6 11.1%	23 42.6%	19 35.2%	4.0	1.1
Composite Mean and SD						**3.8**	**1.2**

Source: Researcher, 2025

From the results, 18(33.3%) of the respondents agreed that AI-based predictive financial modelling forecasts future financial outcomes with greater accuracy. 18(33.3%) strongly concurred with the statement while 8(14.8%) were not decisive with a mean of 3.7 and a respective SD of 1.3 hence on average, the responses were in concurrence. On whether firms using AI in financial modelling can identify profitability trends, the responses indicated that 24(44.4%) of the responses concurred, 5(9.3%) being neutral and 16(29.6%) attracting a strong concurrence with a mean and SD of 3.8 and 1.2.

Furthermore, 24(44.4%) of the responses were in tandem that integrating AI into financial forecasting enhances the precision of cash flow projections. 14(25.9%) recording strong concurrence and 8(14.8%) were not decisive with a mean of 3.8 and a corresponding SD of

1.1 meaning that on average, there was concurrence among the responses. 4(7.4%) of the responses were neutral on whether the use of AI in financial modelling supports more informed investment decisions. Furthermore, 26(48.1%) were in concurrence with 14(25.9%) strongly concurring with a mean and SD of 3.7 and 1.3. Hence, there concurrence among the responses on average.

Concerning the statement, AI models can incorporate a wide range of data including macroeconomic indicators to produce holistic performance forecasts, 23(42.6%) of the participants were in tandem, 21(38.9%) recording a strong agreement with 2(3.7%) being neutral. The mean and SD recorded by the question were 4.0 and 1.2 meaning that, on average the respondents concurred. Finally, 23(42.6%) of the respondents pointed to an agreement that predictive analytics powered by AI enables early detection of financial distress, while 19(35.2%) strongly concurred and 6(11.1%) being neutral with a mean of 4.0 and SD of 1.1 meaning that overage, the respondents were in concurrence.

4.3.2 Descriptive Results for AI-Based Risk Management

A summarized table outlining the descriptive outcomes of the questions on AI-Based risk management is outlined in Table 4.4.

Table 4.4: Descriptive Results for AI-Based Risk Management

	SD	D	N	A	SA		
	N %	N %	N %	N %	N %	M	S Dev
Predictive AI tools contribute to better credit risk assessment	3 5.6%	7 13%	4 7.4%	20 37%	20 37%	3.9	1.2
AI enhances fraud detection capabilities	2 3.7%	9 16.7%	5 9.3%	19 35.2%	19 35.2%	3.8	1.2
AI-driven risk tools optimize capital allocation by quantifying risks more accurately	6 11.1%	4 7.4%	7 13%	19 35.2%	18 33.3%	3.7	1.3
AI can enhance a firm's ability to prepare for economic shocks	6 11.1%	5 9.3%	5 9.3%	20 37%	18 33.3%	3.7	1.3
AI-based risk management systems help firms identify financial risks more effectively by analysing vast datasets in real time	6 11.1%	3 5.6%	9 16.7%	19 35.2%	17 31.5%	3.7	1.3
AI enables reduces the likelihood of financial losses by detecting anomalies and predicting potential threats	7 13%	2 3.7%	6 11.1%	25 46.3%	14 25.9%	3.7	1.3
Composite Mean and SD						**3.8**	**1.3**

Source: Researcher, 2025

From the outcomes, 20(37%) of the respondents agreed that predictive AI tools contribute to better credit risk assessment. However, 20(37%) concurred strongly with the statement while 4(7.4%) were not decisive with a mean of 3.9 and an SD of 1.2 Hence, the responses were in agreement. Regarding whether AI enhances fraud detection capabilities, 19(35.2%) of the responses concurred, 5(9.3%) being neutral and 19(35.2%) were strongly in tandem with a mean and SD of 3.8 and 1.2.

Furthermore, 19(35.2%) of the responses were in agreement that AI-driven risk tools optimize capital allocation by quantifying risks more accurately while 18(33.3%) were strongly in concurrence and 7(13%) were not decisive with a mean of 3.7 and SD was 1.3 meaning that on average, there was concurrence among the responses. Additionally, 5(9.3%) of the responses were moderately in tandem with regards the statement ‘AI can enhance a

firm's ability to prepare for economic shocks’. 20(37%) were in concurrence with 18(33.3%) strongly concurring with a mean and SD of 3.7 and 1.3.

From the statement, AI-based risk management systems help firms identify financial risks more effectively by analysing vast datasets in real time, 19(35.2%) of the participants were in concurrence, 17(31.5%) recording a strong concurrence with 9(16.7%) being neutral. The mean and SD received by the question were 3.7 and 1.3 in that order pointing out that, on average the responses were in tandem. Finally, 25(46.3%) of the responses indicated an agreement that AI enables reduces the likelihood of financial losses by detecting anomalies and predicting potential threats, while 14(25.9%) strongly agreed with the statement and 6(11.1%) being neutral with a mean of 3.7 and SD of 1.3 meaning the responses were in concurrence.

4.3.3 Descriptive Results for AI-Based Portfolio Optimization

A summarized table outlining the descriptive outcomes of the questions on AI-Based portfolio optimization is outlined in Table 4.5.

Table 4.5: Descriptive Results for AI-Based Portfolio Optimization

	SD N %	D N %	N N %	A N %	SA N %	M	S Dev
AI-based portfolio optimization uses advanced algorithms to come up investment portfolios that maximize returns	3 5.6%	9 16.7%	1 1.9%	26 48.1%	15 27.8%	3.8	1.2
AI can dynamically rebalance portfolios in response to market movements	6 11.1%	6 11.1%	4 7.4%	23 42.6%	15 27.8%	3.6	1.3
The use of AI for portfolio management is essential in identifying non-obvious investment opportunities through deep data analysis	5 9.3%	5 9.3%	5 9.3%	23 42.6%	16 29.6%	3.7	1.2
AI tools can process diverse datasets to enhance portfolio decision-making	5 9.3%	4 7.4%	8 14.8%	21 38.9%	16 29.6%	3.7	1.2
AI helps firms adapt quickly to changing market conditions	1 1.9%	7 13%	11 20.4%	23 42.6%	12 22.2%	3.7	1.0
AI-driven portfolio strategies reduce human biases in investment decisions	5 9.3%	6 11.1%	3 5.6%	23 42.6%	17 31.5%	3.8	1.3
Composite Mean and SD						**3.7**	**1.2**

Source: Researcher, 2025

As per the outcomes, 26(48.1%) of the participants were in concurrence that AI-based portfolio optimization uses advanced algorithms to come up investment portfolios that maximize returns. However, 15(27.8%) recorded strong concurrence with the statement while 1(1.9%) were not decisive with a mean of 3.8 and a respective SD of 1.2 an implication that on average, the participants were in tandem. With regards whether AI can dynamically rebalance portfolios in response to market movements, 23(42.6%) of the responses concurred, 4(7.4%) being neutral and 15(27.8%) being in tandem strongly with a mean and SD of 3.6 and 1.3 indicating a concurrence among the responses.

In addition, 23(42.6%) of the responses were in tandem that the use of AI for portfolio management is essential in identifying non-obvious investment opportunities through deep

data analysis while 16(29.6%) recording strong concurrence and 5(9.3%) neutral with a mean of 3.7 and SD was 1.2 meaning that on average, the responses were in tandem. 8(14.8%) of the responses were neutral with regards the statement that AI tools can process diverse datasets to enhance portfolio decision-making. In addition, 21(38.9%) were in tandem with 16(29.6%) concurred strongly with a mean and SD of 3.7 and 1.2. Hence, the responses were in concurrence on average.

On whether AI helps firms adapt quickly to changing market conditions, 23(42.6%) of the responses were in concurrence, 12(22.2%) recording a strong concurrence with 11(20.4%) were not decisive. The mean and the SD attracted by the question were 3.7 and 1.0 in that order meaning that, on average the responses were in tandem. Finally, 23(42.6%) of the respondents were in tandem that AI-driven portfolio strategies reduce human biases in investment decisions, while 17(31.5%) agreed strongly and 3(5.6%) being neutral with a mean of 3.8 and SD of 1.3 meaning an agreement among the responses.

4.3.4 Descriptive Results for AI-Based Fraud Detection

A summarized table outlining the descriptive outcomes of the questions on AI-Based fraud detection is outlined in Table 4.6.

Table 4.6: Descriptive Results for AI-Based Fraud Detection

	SD	D	N	A	SA		
	N %	N %	N %	N %	N %	M	S Dev
AI-based fraud detection systems enhance real time financial security	3 5.6%	3 5.6%	9 16.7%	23 42.6%	16 29.6%	3.9	1.1
AI can detect complex fraud patterns	9 16.7%	2 3.7%	5 9.3%	20 37%	18 33.3%	3.7	1.4
AI systems continuously learn from new fraud tactics	3 5.6%	6 11.1%	4 7.4%	22 40.7%	19 35.2%	3.9	1.2
AI contributes directly to improved profitability and financial performance of firms by reducing fraud-related losses	4 7.4%	5 9.3%	8 14.8%	21 38.9%	16 29.6%	3.7	1.2
Automating fraud monitoring with AI allows firms to allocate resources more efficiently	5 9.3%	4 7.4%	5 9.3%	22 40.7%	18 33.3%	3.8	1.2
Through faster fraud detection and resolution, AI improves customer trust and satisfaction, which supports long-term business growth and financial stability	2 3.7%	6 11.1%	9 16.7%	20 37%	17 31.5%	3.8	1.1
Composite Mean and SD						**3.8**	**1.2**

Source: Researcher, 2025

According to the outcomes, 23(42.6%) of the respondents concurred that AI-based fraud detection systems enhance real time financial security. Further, 16(29.6%) concurred strongly while 9(16.7%) were neutral with a mean of 3.9 and a respective SD of 1.1 meaning that on average, the responses were neutral. With regards to whether AI can detect complex fraud patterns, 20(37%) of the respondents were in tandem, 5(9.3%) being neutral and 18(33.3%) were in tandem strongly with a mean and SD of 3.7 and 1.4 indicating that the responses were in tandem.

Additionally, 22(40.7%) of the responses were in agreement with the question on whether AI systems continuously learn from new fraud tactics while 19(35.2%) concurred strongly and 4(7.4%) were neutral. The mean of the responses was 3.9 and a SD was 1.2 meaning that the responses were in agreement. 8(14.8%) of the responses were neutral with regards the

statement ‘AI contributes directly to improved profitability and financial performance of firms by reducing fraud-related losses’. Furthermore, 21(38.9%) were in agreement with 16(29.6%) strongly agreeing with a mean and SD of 3.7 and 1.2. This means the responses were in tandem on average.

On whether automating fraud monitoring with AI allows firms to allocate resources more efficiently, 22(40.7%) of the participants were in concurrence, 18(33.3%) were in concurrence strongly with 5(9.3%) being neutral with a mean and the SD of 3.8 and 1.2 respectively an meaning that, on average the responses were in concurrence. 20(37%) of the responses were in concurrence that through faster fraud detection and resolution, AI improves customer trust and satisfaction, which supports long-term business growth and financial stability, while 17(31.5%) concurred strongly and 9(16.7%) being neutral with a mean of 3.8 and SD of 1.1 meaning the responses were in tandem.

4.3.5 Descriptive Results for Financial Performance

A summarized table outlining the descriptive outcomes of the questions on financial performance is presented in Table 4.7.

Table 4.7: Descriptive Results for Financial Performance

	SD	D	N	A	SA		
	N %	N %	N %	N %	N %	M	S Dev
The firm is able to generate revenue and achieve profitability over time	6 11.1%	5 9.3%	2 3.7%	26 48.1%	15 27.8%	3.7	1.3
Strong financial performance enables firms to reinvest in operations	6 11.1%	4 7.4%	6 11.1%	20 37%	18 33.3%	3.7	1.3
The is consistency in the financial performance of the firm	3 5.6%	8 14.8%	7 13%	13 24.1%	23 42.6%	3.8	1.3
Effective financial management, is crucial for maintaining strong performance	6 11.1%	2 3.7%	6 11.1%	28 51.9%	12 22.2%	3.7	1.2
Technological adoption and innovation often lead to efficiency gains	6 11.1%	2 3.7%	4 7.4%	25 46.3%	17 31.5%	3.8	1.2
Sustainable financial performance supports long-term business viability and resilience	4 7.4%	4 7.4%	6 11.1%	24 44.4%	16 29.6%	3.8	1.2
Composite Mean and SD						**3.8**	**1.3**

Source: Researcher, 2025

From the results outlined, 26(48.1%) of the respondents concurred that the firm is able to generate revenue and achieve profitability over time. On the other hand, 15(27.8%) concurred strongly while 2(3.7%) were neutral with a mean of 3.7 and a respective SD of 1.3 meaning that on average, the responses were in tandem. Concerning whether strong financial performance enables firms to reinvest in operations, 20(37%) of the respondents were in tandem, 6(11.1%) being neutral and 18(33.3%) were in tandem strongly with an SD of 1.3 and a mean of 3.7.

Furthermore, 13(24.1%) of the responses were in tandem concerning the statement ‘There is consistency in the financial performance of the firm’ while 23(42.6%) recording strong concurrence and 7(13%) neutral. The mean was 3.8 and a SD was 1.3 meaning that on average, the responses were in agreement. 6(11.1%) of the responses were neutral concerning the question ‘Effective financial management, is crucial for maintaining strong performance,

28(51.9%) were in concurrence with 12(22.2%) strongly agreeing with a mean and SD of 3.7 and 1.2 implying concurrence among the responses on average.

Furthermore, 4(7.4%) of the responses were neutral with regards the statement 'Technological adoption and innovation often lead to efficiency gains, 25(46.3%) were in tandem with 17(31.5%) strongly concurring with a mean and SD of 3.8 and 1.2. This gives the implication the responses were in tandem on average. Finally, 24(44.4%) of the respondents agreed that the sustainable financial performance supports long-term business viability and resilience while 6(11.1%) taking a neutral stand and 16(29.6%) indicating a strong agreement with a mean of 3.8 and a SD of 1.2 in that order.

4.4 Diagnostic Tests

Diagnostic tests were conducted to explore if the data collected is suitable to perform other analysis such as regression analysis, which is critical in meeting the objectives of the research. Failure to conduct assumptions of classical linear regression model and diagnostic tests may result to inaccurate parameter estimates of the model. The tests that were conducted include multicollinearity tests, normality tests and the tests for heteroscedasticity.

4.4.1 Multicollinearity

Multicollinearity represents a condition where two or more predictor variables are found to be highly linearly related (Montgomery *et al.*, 2015). One of the variables ought to be eliminated in the study, if two or more variables are correlated highly, as the two variables offer the same explanation on the dependent variable. The study used Variance Inflation Factor (VIF) to measure multicollinearity (Alin,2010). As a decision role, VIF value>0.5 would signal the presence of multicollinearity whereas VIF values <0.5 would absence of multicollinearity.

Table 4.8: Multicollinearity Test Results

	Collinearity Statistics	
	Tolerance	**VIF**
(Constant)		
AI-Based Predictive Financial Modelling	0.759	1.318
AI-Based Risk Management	0.967	1.034
AI-Based Portfolio Optimization	0.789	1.267
AI-Based Fraud Detection	0.918	1.089

Source: Researcher, 2025

From the outcomes, the VIF values for all the study variables are <5 implying the absence of multicollinearity in the data set (1.318<5, 1.034<5, 1.267<5 and 1.089<5). This implies that all the variables were retained in the study for further analysis.

4.4.2 Normality

Normality tests are carried out to ascertain the consistency in the distribution of data (Yazici & Yolacan, 2007). To carry out single or joint hypothesis tests of the model, the normality assumption should be in place (Brooks & Condori, 2018). Normality tests were conducted using Shapiro-Wilk. A computed p-values >0.05 would imply that the data set collected follows normal distribution and hence fit for further analysis (Mishra *et al.*, 2019).

Table 4.9: Normality Test Results

	Shapiro-Wilk		
	Statistic	**df**	**Sig.**
Financial Performance	0.952	54	0.101
AI-Based Predictive Financial Modelling	0.969	54	0.077
AI-Based Risk Management	0.953	54	0.071
AI-Based Portfolio Optimization	0.974	54	0.231
AI-Based Fraud Detection	0.983	54	0.222

Source: Researcher, 2025

It can be observed from the outcomes that all the significance values for the variable in the study are >0.05 (0.101>0.05, 0.077>0.05, 0.071>0.05, 0.231>0.05 and 0.222>0.05). Hence,

the study makes the conclusion that the data follows a normal distribution and hence can be used for further analysis.

4.4.3 Heteroscedasticity

Heteroscedasticity is defined by Carapeto and Holt (2003) as a condition where the variability of a variable is unequal across a range of values of the predicting variable. The test was conducted to ascertain if certain data sets' observations are modified or same or if the error term of a particular variable under review is non-constant. The tests for heteroscedasticity was carried out employing Wooldridge tests. With this method, large Chi2 values would imply the presence of heteroscedasticity (Rosopa *et al.,* 2013).

Table 4.10: Heteroscedasticity Test Results

Ho: Constant variance
Variable: Financial Performance
chi2(1) = 0.137
Prob > chi2 = 0.0743

Source: Researcher, 2025

The outcomes postulate that with a relatively smaller Chi square of 0.137, then the results imply that heteroscedasticity is absent.

4.5 Inferential Statistics

Inferential analysis of the investigation included regression and correlation analysis.

4.5.1 Correlation Results

This serves to explore the direction and strength of association between AI-based business models including AI-based predictive financial modelling, AI-based risk management, AI-based portfolio optimization and AI-based fraud detection and financial performance of listed entities under review. Tale 4.11 shows the correlation outcomes.

Table 4.11: Correlation Results

		Financial Performance	AI-Based Predictive Financial Modelling	AI-Based Risk Management	AI-Based Portfolio Optimization	AI-Based Fraud Detection
Financial Performance	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	54				
AI-Based Predictive Financial Modelling	Pearson Correlation	.555**	1			
	Sig. (2-tailed)	0.000				
	N	54	54			
AI-Based Risk Management	Pearson Correlation	.562**	0.068	1		
	Sig. (2-tailed)	0.000	0.025			
	N	54	54	54		
AI-Based Portfolio Optimization	Pearson Correlation	.564**	.457**	0.072	1	
	Sig. (2-tailed)	0.000	0.001	0.005		
	N	54	54	54	54	
AI-Based Fraud Detection	Pearson Correlation	.567**	0.238	0.175	0.13	1
	Sig. (2-tailed)	0.000	0.004	0.006	0.049	
	N	54	54	54	54	54

Source: Researcher, 2025

From the association outcomes, the correlation between financial performance of the firms listed at NSE and AI-Based Predictive Financial Modelling was positive (0.555) and significant statistically ($p=0.000<0.05$). This means that AI-Based Predictive Financial Modelling determines performance significantly.

The relationship between financial performance of the entities listed at NSE and AI-Based risk management was positive (0.562) and significant (p=0.000<0.05). This means that AI-Based risk management determines performance significantly.

The correlation between performance of the entities under investigation and AI-Based portfolio optimization was significant (p=0.000<0.05) and positive (0.564). This means that AI-Based portfolio optimization determines performance significantly.

The correlation between financial performance of the entities listed at NSE and AI-Based fraud detection was significant statistically (p = 0.000 < 0.05) and positive (0.567). This means that AI-Based fraud detection is a significant determinant of financial performance.

4.5.2 Regression Analysis

This is conducted to determine the linear relationship between e AI-based business models including on AI-based predictive financial modelling, AI-based risk management, AI-based portfolio optimization and AI-based fraud detection and financial performance of listed entities in Nairobi Securities Exchange.

Table 4.12: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.906a	0.820	0.806	0.46278

Source: Researcher, 2025

From the outcomes of the estimated model, the variables under study including AI-based predictive financial modelling, AI-based risk management, AI-based portfolio optimization and AI-based fraud detection explain to a tune of 82% of the total variations in financial performance of listed firms under investigation. Thus, the variables under investigation are significant determinants of financial performance.

Table 4.13: ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	47.923	4	11.981	55.942	.000b
Residual	10.494	49	0.214		
Total	58.417	53			

Source: Researcher, 2025

From the ANOVA outcomes, the estimated model is significant statistically. This is because the significance value is 0.000<0.05 and the calculated F value (55.942) is greater than the F critical values from the F tables (2.3683) under the same degrees of freedom. Thus, the results of the estimated model can be used to make reliable inferences.

Table 4.14: Multiple Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.918	0.388		4.945	0.000
AI-Based Predictive Financial Modelling	0.321	0.083	0.27	3.888	0.000
AI-Based Risk Management	0.472	0.064	0.452	7.339	0.000
AI-Based Portfolio Optimization	0.420	0.08	0.359	5.271	0.000
AI-Based Fraud Detection	0.401	0.067	0.377	5.967	0.000

Source: Researcher, 2025

The coefficient of AI-Based predictive financial modelling was positive (0.321) and significant statistically ($p = 0.000 < 0.05$). Thus, a unit increase in AI-Based predictive financial modelling results in 0.321 units increase in performance of listed entities under investigation. Thus, AI-Based predictive financial modelling is a significant determinant of financial performance. The results are consistent with the findings of Kang and Park (2021) which pointed out that over the last decade, there have been substantial increase in the adoption AI applications including machine learning attributed to the advancements in computer volume and growth of data volume. The adoption of these technologies enhances the accuracy of the model compared to conventional linear regression models.

Wamba-Taguimdje et al. (2020) further indicated that a range of technologies are covered by AI models for example machine translations, self-learning algorithms and chatbots which allow individuals to understand and act accordingly in their environments. The adoption of AI technological innovations by firms is aimed at enhancing their competitive advantage and further developing and optimizing strategic advantages. AI serves to improve automation, transformation and information and optimize existing processes. Ho et al. (2022) also indicated the negative impact of Covid-19 was more severe on conventional stock markets in the first month of the pandemic than on AI-stock market. However, when financial market

was exposed to the uncertainties of the pandemic, conventional stocks were less resilient. AI deployment is a crucial driver of sustainable performance in environments characterized by challenges. Shiyyab et al. (2023) indicated that AI positively affects accounting performance and its effect on total expenses was negative. The performance of banks is affected by AI related keywords and disclosures though for AI related disclosures, it was weak for some banks. Agarwall et al. (2022) indicated that AI significantly influences operating profit and cost of the companies under investigation.

The coefficient of AI-Based risk management was significant statistically ($p= 0.000 < 0.05$) and positive (0.472). Thus, a unit increase in AI-Based risk management results in 0.472 units increase in performance of listed entities under review. Thus, AI-Based risk management is a significant determinant of financial performance. The results concur with the findings of Abrokwa-Larbi and Awuku-Labi (2024) postulated that in marketing, AI significantly impacts learning and growth, internal business process and financial performance with regards Ghanaian SMEs.

Al-Sumi et al. (2022) also pointed out that firm structure moderates the mediation of strategy of marketing on performance while marketing strategy positively mediates on IT strategy and performance. The use of novel three-phase decision-making framework enhances decision accuracy, increases insights and improves operational efficiency at strategic levels in industries. Liu et al. (2024) further pointed out that entities are continuously increasing investments to boost efficiency, lower costs and boost revenues. The results of the investigation were however mixed regarding AI project adoption.

In addition, the findings of Caner (2024) indicated a positively significant correlation between perceived business performance and implementation of AI. The investigation concluded that the adoption of AI could be significant in improving performance of businesses, however, with regards TDZs in Turkiye, its effect is modest. Chen et al. (2023)

indicated that normative pressure, the support from top management and technological opportunism are the primary drivers behind the intensity of adoption of AI. Increasing intensity in AI adoption improves the marketing performance of entities significantly as it enhances the capabilities to cop with the ever changing and dynamic businesses arena.

The coefficient of AI-Based portfolio optimization was positive (0.420) and significant statistically ($p= 0.000 < 0.05$). Thus, improving AI-Based portfolio optimization by a unit leads to 0.420 units increase in performance of listed entities under investigation. Thus, AI-Based portfolio optimization is a significant determinant of financial performance. The outcomes concur with the findings of Li et al. (2024) indicate that adoption of AI significantly reduces the likelihood of risk of stock price crash. The adoption of AI contributes to reduction in firm SPCR as it enhances the quality of internal control. This association is greater on non-SOEs compared to SOEs. Faqihi and Miah (2023) indicated that the functionalities of AI can be significant in assisting professional talent managers by investigating, predicting and identifying talent management and trends related to performance. AI can be resourceful in developing chatbots which frequently answers questions on resumes, job applications and careers.

In addition, the findings of Saffari (2024) indicated that the integration of AI and MCDM provides a promising approach for enhancing the effectiveness of business risk management. By leveraging AI's data-driven analysis and predictive capabilities alongside the structured decision-making framework of MCDM, organizations can gain a deeper comprehension of the evolving risk landscape and make more informed strategic decisions. Paul et al. (2021) pointed out that the factors under review recorded varying degrees of influence on AI adoption in SCRM. Kanti et al. (2022) also argued that the adoption of AI is necessary considering emergence of pandemic led disruptions from global and local supply chains and operations.

The coefficient of AI-Based fraud detection was significant statistically ($p=0.000<0.05$) and positive (0.401). Thus, a unit increase in AI-Based fraud detection results in 0.401 units increase in financial performance of listed entities in Nairobi Securities Exchange. Thus, AI-Based fraud detection determines performance significantly. The outcomes are in concurrence with the findings of Narsina et al. (2019) which pointed out that AI improves fraud detection by identifying complex patterns, reacting to new risks, and increasing transaction efficiency via automation, intelligent routing, and real-time optimization. These innovations speed up transaction processing, save operating expenses, and minimize fraud losses. Hussain et al. (2025) argued out a positive association between AI tools implementation for detection of fraud, enhanced decision abilities and risk management in overall. There was improvement in timeliness and accuracy to fulfill the regulatory compliance needs.

Further, Mohammed and Rahman (2024) indicated that by incorporating data analytics, machine learning algorithms and AI models, firms can identify and mitigate fraudulent activities effectively and hence protecting reputation and financial assets. Yuhertiana and Amin (2024) demonstrated that adoption of AI techniques of fraud detection have proven effective and precise in identification of fraud pattern. Aljunaid et al. (2025) indicated that while AI improves the detection of fraud, its nature makes it difficult for users to refine, validate and trust decisions posing challenges for adversarial defense and fraud explanation. Federated learning ensures legal compliance, preserves data privacy and enables distributed training for detection of fraud.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

A summary of the outcomes in the investigation, the conclusions and recommendations are outlined in the section. The section is also organized as per the objectives under review.

5.1 Summary

The section is organized objectively.

5.1.1 AI-Based Predictive Financial Modelling and Financial Performance

From the correlation results, the correlation between performance of the entities listed at NSE and AI-Based Predictive Financial Modelling was significant statistically ($p=0.000<0.05$) and positive (0.555). The coefficient of AI-Based predictive financial modelling was positive (0.321) and significant statistically ($p=0.000<0.05$). Thus, a unit increase in AI-Based predictive financial modelling results in 0.321 units increase in financial performance of listed firms in Nairobi Securities Exchange. Thus, AI-Based predictive financial modelling determines performance significantly.

5.1.2 AI-Based Risk Management and Financial Performance

The correlation between financial performance of the entities listed at NSE and AI-Based risk management was positive (0.562) and significant statistically ($p=0.000<0.05$). The coefficient of AI-Based risk management was positive (0.472) and significant statistically ($p=0.000<0.05$). Thus, a unit increase in AI-Based risk management results in 0.472 units increase in financial performance of listed entities in Nairobi Securities Exchange. Thus, AI-Based risk management determines performance significantly.

5.1.3 AI-Based Portfolio Optimization and Financial Performance

The correlation between financial performance of the firms listed at NSE and AI-Based portfolio optimization was positive (0.564) and significant statistically ($p=0.000 < 0.05$). The coefficient of AI-Based portfolio optimization was positive (0.420) and significant statistically ($p=0.000 < 0.05$). Thus, a unit increase in AI-Based portfolio optimization results in 0.420 units increase in performance of listed entities in Nairobi Securities Exchange. Thus, AI-Based portfolio optimization is a significant determinant of performance.

5.1.4 AI-Based Fraud Detection and Financial Performance

The correlation between financial performance of the entities listed at NSE and AI-Based fraud detection was positive (0.567) and significant statistically ($p=0.000<0.05$). The coefficient of AI-Based fraud detection was positive (0.401) and significant statistically ($p=0.000<0.05$). Thus, a unit increase in AI-Based fraud detection results in 0.401 units increase in performance of listed entities in Nairobi Securities Exchange. Thus, AI-Based fraud detection determines significantly financial performance.

5.2 Conclusions

The coefficient of AI-Based predictive financial modelling was positive and significant statistically. Thus, a unit increase in AI-Based predictive financial modelling results in significant units increase in performance of listed entities in Nairobi Securities Exchange. Thus, AI-Based predictive financial modelling has a significant positive nexus with financial performance. AI-based predictive financial modelling has is significant for enhancing financial performance by leveraging advanced algorithms and machine learning to forecast trends, detect anomalies and optimize decision-making with high levels of accuracy. AI models can identify patterns and correlations, enabling organizations to anticipate market shifts, manage risks proactively and allocate resources more efficiently.

The coefficient of AI-Based risk management was significant statistically and positive. Thus, a unit increase in AI-Based risk management results in significant units increase in financial performance of listed entities at NSE. Thus, AI-Based risk management has a significant positive link with performance. AI-based risk management enables entities to mitigate, identify and assess risks with greater speed and accuracy. Through real-time data analysis, predictive modeling, and automated anomaly detection, AI systems help firms anticipate potential threats, reduce losses, and ensure regulatory compliance more effectively.

The coefficient of AI-Based portfolio optimization was positive and significant statistically. Thus, increasing AI-Based portfolio optimization by a unit result in significant units increase in financial performance of listed firms in Nairobi Securities Exchange. Thus, AI-Based portfolio optimization has a significant positive association with financial performance. AI-based portfolio optimization enables institutions to construct and adjust portfolios with a level of precision and adaptability unattainable through conventional methods. AI algorithms can dynamically balance risk and return in real time, respond swiftly to changing market conditions and determine investment opportunities that maximize profitability.

The coefficient of AI-Based fraud detection was significant statistically and positive. Thus, a unit increase in AI-Based fraud detection results in significant units increase in financial performance of entities listed in Nairobi Securities Exchange. Thus, AI-Based fraud detection significant positive link with financial performance. AI-based fraud detection empowers organizations to identify and prevent fraudulent activities with unmatched accuracy and speed. The technology leverages on real time data analytics and machine learning and can detect subtle anomalies and suspicious patterns thus significantly reducing financial losses and safeguarding assets. This proactive defense not only minimizes the direct costs of fraud but also protects customer trust, strengthens regulatory compliance, and frees up resources for strategic growth initiatives.

5.3 Recommendations

5.3.1 Recommendations to Practice

The investigation recommends that the firms listed at NSE ought to adopt AI-based predictive financial modelling as a strategic priority to enhance their financial performance as it improves the accuracy and timeliness of forecasting, budgeting and investment decisions. This enables the firms to get deeper insights into market trends, customer behavior and emerging risks, enabling more agile responses to changing conditions.

The listed firms under study should also prioritize the integration of AI-based risk management systems to strengthen their financial performance. AI-based risk management enables faster, more precise identification and mitigation of operational, credit and market risks and hence allows firms to detect emerging threats in real time, model complex scenarios and make data-driven decisions that reduce potential losses and enhance resilience.

The firms under study should also adopt AI-based portfolio optimization tools to enhance financial performance as it maximizes returns while effectively managing risk across diverse asset classes. The firms can be able to identify subtle patterns, forecast market movements and dynamically adjust portfolio allocations with greater speed and precision.

Finally, the investigation recommends that the listed entities under investigation should implement AI-based fraud detection systems to strengthen financial performance. The systems safeguard revenues, protecting stakeholder trust and minimizing losses due to fraudulent activities. It also enables the firms to detect complex fraud patterns and anomalies far more accurately and swiftly.

5.3.2 Recommendations to Policy

The study further recommends that ought to develop a supportive regulatory framework that encourages the adoption of AI-Business models by the listed firms under study to enhance

performance. The framework should have clear guidelines on ethical AI use and data privacy among other critical components to build public trust while enabling innovation. Encouraging adoption of AI business models enables improved decision making by the firms, reducing costs and hence boosting profitability.

5.4 Recommendations for Further Studies

The section covers the contributions of results to knowledge and also areas for further investigation.

5.4.1 Contributions to Knowledge

The results of the study support the propositions of Diffusion of Innovation Theory postulated by Rogers in 1962 and states that innovation is the spontaneous dispersion of ideas. The theory provides an understanding on the patterns, speed and how practices, products or ideas spread across the population. Hence, the theory explains how the adoption of AI-supported business-based models including AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection are significant in enhancing the performance of the entities listed at NSE.

In addition, the outcomes support the propositions of Technology-Organization-Environment Framework (TOE) developed by Louis G. Tornatzky and Mitchell Fleischer in 1990 to provide an understanding on various factors influencing technological adoption and use such as the external environment under which the firm operates, the firm context in which technology is used as well as the characteristics of the technology itself. The framework underlines the factors influencing technological adoption by listed firms including technological, organizational and environmental factors. These factors are also particularly important in explaining the adoption of AI-based models among listed firms at NSE considering the rapid penetration of advanced information technologies.

Finally, the findings support the propositions of Technology Acceptance Model introduced by Fred Davis in 1989 (Davis, 1989). The theory postulates the presence of two factors that are key determinants of the adoption or acceptance of any particular computer system including whether the system is useful as well as its perceived easy usage. The theory explains how the adoption of AI-supported business-based models including AI-based predictive financial modelling, risk management, portfolio optimization and fraud detection are significant in enhancing the performance of the entities listed at NSE.

5.4.2 Areas for Further Research

Future research on artificial intelligence-based business models and financial performance of listed firms in the NSE could explore several promising areas. These include examining the sector-specific impacts of AI adoption, such as in banking, manufacturing, or agriculture, and how AI integration affects firm-level performance metrics like return on equity, profitability, or market valuation. Researchers could also investigate the role of organizational readiness, digital infrastructure, and regulatory environment in shaping the success of AI-driven models. Additionally, longitudinal studies tracking pre- and post-AI adoption financial outcomes would provide deeper insights into causality.

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APPENDICES

Appendix I: Introductory Letter

Dear Respondent,

I am conducting a study on AI-based business models and financial performance of listed firms in the Nairobi Securities Exchange for the award of the degree of master of business administration in e-commerce, school of business. Attached is a questionnaire, kindly answer all the questions with your own level of agreement to each. There are no wrong responses for any of these statements. All information given in the questionnaire will be treated with strict confidentiality and used for the purpose of this research only.

Thank you for taking your time to fill in the questionnaire.

Yours Sincerely,

Brenda Wangui Muchiri

Appendix II: Questionnaire

The questionnaire is meant for collecting information to determine **the effect of AI-based business models on financial performance of listed firms in Nairobi Securities Exchange**. The information to be collected is for purpose of academic research and will not be used for any commercial use.

INSTRUCTIONS

Tick (√) as appropriate.

SECTION A: DEMOGRAPHIC INFORMATION

1. Which department do you work in?

Marketing	[ ]	Business development	[ ]
Human resource	[ ]	Operations	[ ]

2. What is the level of adoption of AI-Based business models in the department you work in?

Low	[ ]	Moderate	[ ]
Fully adopted	[ ]		

3. How long have you been working your firm?

Less than 5 Yrs	[ ]	More than 5 yrs	[ ]

4. Are AI-Based business models beneficial on the financial performance of your firm?

Yes	[ ]	No	[ ]
Maybe	[ ]		

Section B: AI-Based Predictive Financial Modelling

5. In the Likert Table, fill the questionnaire by ticking (√) appropriately. Indicate the extent to which the following aspects of AI-based predictive financial modelling affect the financial performance of firms listed at NSE. Using Likert scale of 1-5 where 1=Strongly Disagree, 2=Disagree, 3=Neutral 4=Agree and 5=Strongly Agree.

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a	AI-based predictive financial modelling forecasts future financial outcomes with greater accuracy					
b	Firms using AI in financial modelling can identify profitability trends					
c	Integrating AI into financial forecasting enhances the precision of cash flow projections					
d	The use of AI in financial modelling supports more informed investment decisions					
e	AI models can incorporate a wide range of data including macroeconomic indicators to produce holistic performance forecasts					
f	Predictive analytics powered by AI enables early detection of financial distress					

Section C: AI-Based Risk Management

6. In the Likert Table, fill the questionnaire by ticking (√) appropriately. Indicate the extent to which the following aspects of AI-based risk management affect the financial performance of firms listed at NSE. Using Likert scale of 1-5 where 1=Strongly Disagree, 2=Disagree, 3=Neutral 4=Agree and 5=Strongly Agree.

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a	Predictive AI tools contribute to better credit risk assessment					
b	AI enhances fraud detection capabilities					
c	AI-driven risk tools optimize capital allocation by quantifying risks more accurately					
d	AI can enhance a firm's ability to					

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	prepare for economic shocks					
e	AI-based risk management systems help firms identify financial risks more effectively by analysing vast datasets in real time					
f	AI enables reduces the likelihood of financial losses by detecting anomalies and predicting potential threats					

Section D: AI-Based Portfolio Optimization

7. In the Likert Table, fill the questionnaire by ticking (√) appropriately. Indicate the extent to which the following aspects of AI-based portfolio optimization affect the financial performance of firms listed at NSE. Using Likert scale of 1-5 where 1=Strongly Disagree, 2=Disagree, 3=Neutral 4=Agree and 5=Strongly Agree.

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a	AI-based portfolio optimization uses advanced algorithms to come up investment portfolios that maximize returns					
b	AI can dynamically rebalance portfolios in response to market movements					
c	The use of AI for portfolio management is essential in identifying non-obvious investment opportunities through deep data analysis					
d	AI tools can process diverse datasets to enhance portfolio decision-making					
e	AI helps firms adapt quickly to changing market conditions					
f	AI-driven portfolio strategies reduce human biases in investment decisions					

Section E: AI-Based Fraud Detection

8. In the Likert Table, fill the questionnaire by ticking (√) appropriately. Indicate the extent to which the following aspects of AI-based fraud detection affect the financial performance of firms listed at NSE. Using Likert scale of 1-5 where 1=Strongly Disagree, 2=Disagree, 3=Neutral 4=Agree and 5=Strongly Agree.

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a	AI-based fraud detection systems enhance real time financial security					
b	AI can detect complex fraud patterns					
c	AI systems continuously learn from new fraud tactics					
d	AI contributes directly to improved profitability and financial performance of firms by reducing fraud-related losses					
e	Automating fraud monitoring with AI allows firms to allocate resources more efficiently					
f	Through faster fraud detection and resolution, AI improves customer trust and satisfaction, which supports long-term business growth and financial stability					

Section F: Financial Performance of Firms Listed at NSE

In the Likert Table, fill the questionnaire by ticking (√) appropriately. Indicate the extent to which the following aspects of financial performance of firms listed at NSE. Using Likert scale of 1-5 where 1=Strongly Disagree, 2=Disagree, 3=Neutral 4=Agree and 5=Strongly Agree.

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a	The firm is able to generate revenue and achieve profitability over time					
b	Strong financial performance enables firms to reinvest in operations					
c	The is consistency in the financial performance of the firm					

#	Statements	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
d	Effective financial management, is crucial for maintaining strong performance					
e	Technological adoption and innovation often lead to efficiency gains					
f	Sustainable financial performance supports long-term business viability and resilience					

THANK YOU

Appendix III: Secondary Data Collection Template

Firm	Year	Total Assets	Net Income
	2024		
	2023		
	2022		
	2021		
	2020		

Appendix IV: Work plan

Activity	**Feb 2025**	**March 2025**	**April 2025**	**May 2025**	**June 2025**	**July 2025**	**Aug 2025**	**Sept 2025**
Proposal development								
Presenting								
Pilot study								
Data collection								
Data cleaning and coding								
Data analysis								
Updating the document								
Submission								

Appendix V: Research budget

Item list	Quantity Description	Quantity	Unit Price - Kshs	copies/number of items	Cost- Kshs
Printing	copies	50	10	3	1,500
Photocopying	copies	50	10	3	1,500
Biding the booklets	copies	6	140	-	840
Data bundle and internet services	hours	90 days	ksh. 50 per hour per day	-	4,350
Collecting data	Field officers	2	20,000	-	40,000
Miscellaneous 10%					10,000
Total					**58,190**

Appendix VI: Plagiarism Report

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I HEREBY CONFIRM THAT **BRENDA WANGUI MUCHIRI** REG NO: **1046350**, SUBMITTED A CHECK OF ANTIPLAGIARISM ON CRITICAL EVALUATION OF **AI-BASED BUSINESS MODELS AND FINANCIAL PERFORMANCE OF LISTED FIRMS IN THE NAIROBI STOCK EXCHANGE. A PROPOSAL SUBMMITED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTERS OF BUSINESS ADMINISTRATION (FINANCIAL MANAGEMENT OPTION) AT THE CATHOLIC UNIVERSITY OF EASTERN AFRICA.**

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Appendix VII: Financial Listed Firms

1. KCB Group Ltd
2. NCBA Group Plc
3. DTB
4. HF Group Ltd
5. BK Group Ltd
6. Cooperative Bank of Kenya Ltd
7. Equity Group Holdings
8. Standard Chartered Bank
9. I&M Holdings
10. Stanbic Holdings
11. Absa Bank Kenya
12. Jubilee Insurance
13. Sanlam Kenya
14. Kenya Re-Insurance Corporation Ltd
15. Liberty Kenya Holdings Ltd
16. Britam
17. CIC Insurance Group Ltd