ARTIFICIAL INTELLIGENCE AND FINANCIAL DECISION-MAKING IN MANUFACTURING FIRMS IN NAIROBI COUNTY, KENYA

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MASTER OF BUSINESS ADMINSTRATION (CORPORATE MANAGEMENT)

KCA UNIVERSITY

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NOVEMBER 2025

DECLARATION

I declare that this dissertation is my original work and has not been previously published or submitted elsewhere for award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and author duly acknowledged.

……  …… ……15/10/2025……

PETER MUTUA KITUU Date

21/03562

I do hereby confirm that I have examined the master's dissertation of

Peter Mutua Kituu

And have certified that all revisions that the dissertation panel and examiners recommended have been adequately addressed.

……  …… -----15/10/2025----------

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ABSTRACT

This study investigated the effect of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya, addressing the gap in understanding how AI tools influence financial strategies despite their growing adoption in business operations. With manufacturing firms facing intricate financial challenges, AI's potential to enhance efficiency, accuracy, and planning remains underexplored locally. The general objective was to establish AI's impact on financial decision-making, with specific objectives to assess the influence of predictive analytics, evaluate the role of machine learning models, examine the impact of automated financial reporting, and determine the effect of natural language processing tools on these processes. The study was guided by four theories: the Technology Acceptance Model, the Resource-Based View; the Automation Theory; and the Cognitive Fit Theory. The study adopted a descriptive cross-sectional survey design. The target population of this study were all the 2752 manufacturing firms in Nairobi County, Kenya. A sample of 349 was arrived at using Yamane formula. The unit of observation was the finance manager in each firm. Questionnaire was utilized in primary data collection. Data was analyzed using descriptive and inferential statistics, including correlation and regression analysis. The regression results revealed that 77.7 percent of the variation in financial decision-making was explained by the four AI dimensions. The model was statistically significant ($F = 207.497$, $p < 0.05$). Regression coefficients showed that all four dimensions had significant positive effects on financial decision-making: predictive analytics ($\beta = 0.325$, $p < 0.001$), machine learning models ($\beta = 0.349$, $p < 0.001$), automated financial reporting ($\beta = 0.206$, $p < 0.001$), and natural language processing tools ($\beta = 0.128$, $p = 0.001$). The study concluded that artificial intelligence significantly enhances financial decision-making by improving budgeting, investment planning, cost management, and risk assessment. The study recommends that manufacturing firms increase investments in AI tools to strengthen decision-making efficiency and accuracy. Managers should prioritize the integration of predictive analytics and machine learning into financial processes while expanding the use of automation for accurate and timely reporting. Firms are also encouraged to adopt NLP tools to reduce cognitive load in financial analysis and improve policy interpretation. Policymakers and industry associations should provide supportive frameworks and incentives to enhance AI adoption across firms, thereby strengthening competitiveness and resilience in the manufacturing sector.

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DEDICATION

This work is dedicated to my family for their unwavering love, encouragement, and support throughout my academic journey. Their sacrifices and belief in my potential have been a constant source of strength and motivation. I also dedicate this study to all finance professionals who continue to embrace innovation and technology in their pursuit of excellence in decision-making.

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ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
CFT	Cognitive Fit Theory
CLRM	Classical Linear Regression Model
ERP	Enterprise Resource Planning
GDP	Gross Domestic Product
GOK	Government of Kenya
ML	Machine Learning
NACOSTI	National Commission for Science, Technology, and Innovation
NLP	Natural Language Processing
RBV	Resource Based View
TAM	Technology Acceptance Model
VRIN	Valuable, Rare, Inimitable, and Non-Substitutable

DEFINITION OF TERMS

Artificial Intelligence	The simulation of human intelligence by machines, including learning, reasoning, and problem-solving, applied to enhance financial decision-making in manufacturing firms (Ahmed et al., 2025).
Automated Financial Reporting	The use of software and AI systems to generate financial reports automatically, reducing manual effort and improving accuracy and timeliness in manufacturing firms (Oyewole et al., 2024).
Financial Decision-Making	The process of making strategic choices regarding resource allocation, investments, and cost management in manufacturing firms, influenced by AI technologies (Alao et al., 2024).
Machine Learning Models	Algorithms that enable systems to learn from data and improve performance over time, used to optimize financial decisions in manufacturing firms (Sharifani & Amini, 2023).
Natural Language Processing Tools	AI tools that process and interpret human language, aiding in the analysis of financial documents and communication for decision-making in manufacturing firms (Fanni et al., 2023).
Predictive Analytics	The use of statistical techniques and AI to analyze historical data and forecast future financial trends or outcomes in manufacturing firms (Okeleke et al., 2024).

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Globally, Artificial Intelligence (AI) has revolutionized financial decision-making across industries, with manufacturing firms increasingly relying on it to navigate complex economic landscapes. The adoption of AI tools, such as predictive analytics and machine learning, has enabled firms to optimize resource allocation, reduce operational costs, and enhance profitability in dynamic markets (Ahmed et al., 2025). These technologies have streamlined processes like budgeting, forecasting, and risk assessment, allowing companies to make data-driven decisions with greater precision (Ocran et al., 2024). Despite this progress, the effectiveness of AI varies widely depending on organizational size, technological infrastructure, and regional economic conditions (Wang et al., 2025). For instance, large multinational manufacturers in developed economies have reported significant gains, while smaller firms in emerging markets struggle to integrate AI effectively (Hossain et al., 2022).

In the African regional context, the manufacturing sector is pivotal for economic development, yet AI adoption remains uneven due to infrastructural limitations and a shortage of skilled personnel. Research indicates that African firms are beginning to explore AI to improve operational efficiency, with financial decision-making emerging as a promising area (Akoh, 2024). However, the continent's digital divide restricts access to advanced technologies, leaving many manufacturers unable to fully harness AI's potential (Amankwah-Amoah & Lu, 2024). In West Africa, where industrialization is a priority, the use of AI tools like automated financial reporting is growing, but its impact on financial outcomes is not well-documented (Oyeniyi et al., 2024). This lag in adoption and evaluation

is particularly evident when compared to global leaders, raising questions about how AI can be tailored to address regional challenges such as volatile markets and limited capital (Nwokolo et al., 2023). Consequently, there is a pressing need to investigate AI's role in enhancing financial decision-making within Africa's unique manufacturing landscape.

Focusing on Kenya, the manufacturing sector is a cornerstone of the economy, contributing about 10% to the national GDP (Kiptum, 2021), with Nairobi County serving as the country's industrial epicenter. The Kenyan government's Vision 2030 initiative emphasizes technological innovation, including AI, as a driver of industrial growth and competitiveness (Koech, 2022). Studies show that manufacturing firms in Kenya are gradually adopting AI to address financial challenges like cost management and investment planning (Tsuma, 2025). However, the specific influence of AI on financial decision-making remains largely uncharted, despite its potential to transform how firms operate in a competitive environment (Wandeda & Were, 2023). Nairobi-based firms, in particular, face pressures from rapid urbanization, rising production costs, and global market integration, which AI could mitigate if properly understood (Ogutu, 2024). The lack of localized research on AI's financial applications in this sector highlights a significant gap that warrants further exploration.

Within Nairobi County, manufacturing firms encounter unique financial pressures, including fluctuating raw material prices, high energy costs, and the need for efficient capital allocation, all of which AI could potentially address. Preliminary evidence suggests that tools like predictive analytics and natural language processing might improve decision-making by providing actionable insights and simplifying data interpretation (Mwaura, 2022). Yet, there is scant empirical data on how these technologies are implemented or their actual impact on financial performance in this specific area (Ogutu, 2024). Moreover,

while automated financial reporting could enhance transparency and speed, its adoption rate and effectiveness among Nairobi's manufacturers remain unclear (Wandeda & Were, 2023). This absence of detailed studies leaves a critical knowledge gap, as firms risk underutilizing AI without evidence-based guidance tailored to their context (Tsuma, 2025). Such uncertainties underscore the necessity for a focused investigation into AI's role in this industrial hub.

These global, regional, and local knowledge gaps collectively justify the current study, as they reveal a disconnect between AI's recognized potential and its practical application in Nairobi County's manufacturing firms. Globally, AI's benefits are evident, but their relevance to emerging markets like Kenya is less certain (Ocran et al., 2024). Regionally, Africa's slow AI uptake and lack of sector-specific research limit its strategic use in manufacturing (Amankwah-Amoah & Lu, 2024). Locally, the absence of data on how specific AI tools influence financial decision-making in Nairobi leaves firms without a clear roadmap for adoption (Ogutu, 2024). This study aims to address these deficiencies by examining AI's impact in this precise context, setting the stage for a problem statement that tackles the underexplored intersection of AI and financial decision-making in Nairobi County's manufacturing sector.

1.1.1 Artificial Intelligence

Artificial intelligence refers to the development of computer systems that mimic human intelligence, enabling tasks such as learning, reasoning, and problem-solving, which are increasingly vital in financial decision-making within manufacturing firms. Globally, AI has transformed how businesses process data and make strategic choices, offering tools that enhance efficiency and accuracy in complex environments (Ocran et al., 2024). In manufacturing, where financial decisions involve cost management, investment planning,

and risk assessment, AI provides a competitive edge by automating processes and generating insights from vast datasets (Hossain et al., 2022). This study focuses on four specific AI measures predictive analytics, machine learning models, automated financial reporting, and natural language processing tools selected for their relevance to financial outcomes in Nairobi County's manufacturing sector (Eng'airo, 2024). These measures are justified by their proven ability to address industry-specific challenges, yet their localized impact remains underexplored, necessitating targeted research.

Predictive analytics, the first measure, involves using statistical algorithms and AI to analyze historical data and forecast future trends, making it essential for financial planning in manufacturing. This tool allows firms to anticipate market shifts, optimize inventory, and predict cash flow needs, thereby reducing uncertainty in decision-making (Ogalloh, 2023). For instance, manufacturers can use predictive analytics to estimate production costs under varying economic conditions, a critical capability in Nairobi's volatile market (Akoh, 2024). Its inclusion in this study is justified by its widespread adoption in global manufacturing and its potential to enhance strategic financial decisions, though its effectiveness in Kenya's context lacks empirical validation (Oyeniyi et al., 2024). Understanding its influence could guide firms in leveraging data-driven foresight effectively.

Machine learning models, the second measure, are algorithms that learn from data and improve over time without explicit programming, offering manufacturing firms a dynamic tool for financial optimization. These models can identify patterns in financial data, such as cost inefficiencies or revenue trends, enabling firms to refine budgeting and investment strategies (Jawad & Balázs, 2024). In Nairobi County, where firms face resource constraints, machine learning could prioritize spending by analyzing past

performance, yet its application remains limited and poorly studied (Wandeda & Were, 2023). This measure is selected because of its adaptability to complex datasets and its growing use in global manufacturing, warranting investigation into how it shapes financial decisions locally (Eng'airo, 2024). Its potential to evolve with firm-specific needs makes it a compelling focus for this research.

Automated financial reporting, the third measure, refers to AI-driven systems that generate financial statements and reports with minimal human intervention, improving speed and transparency in manufacturing firms. This tool reduces errors in financial documentation, ensures compliance with regulations, and provides real-time insights for decision-makers (Alao et al., 2024). In Nairobi, where manufacturing firms must manage tight margins and report to stakeholders efficiently, automation could streamline processes, but its adoption rate and impact are unclear (Ogalloh, 2023). Its inclusion is justified by its ability to enhance accountability and its rising prominence in global financial management, though local evidence is scarce (Ogutu, 2024). Examining this measure will reveal its practical value in a resource-constrained setting.

Natural Language Processing (NLP) tools, the fourth measure, enable machines to interpret and analyze human language, facilitating the extraction of financial insights from unstructured data like reports or contracts. In manufacturing, NLP can simplify the review of financial documents, identify key terms, and support communication with stakeholders, enhancing decision-making efficiency (Mwachikoka, 2024). For Nairobi's firms, where manual analysis of financial texts is time-consuming, NLP offers a scalable solution, yet its implementation and benefits are under-researched (Kariuki, 2023). This measure is chosen for its ability to bridge data interpretation gaps and its increasing relevance in AI applications, justifying a study to assess its role in financial contexts (Ogalloh, 2023).

Together, these four measures provide a comprehensive framework to explore AI's impact on financial decision-making in this study.

1.1.2 Firm Financial Decision-Making

Firm financial decision-making in manufacturing sector involves the strategic process of making choices about how financial resources are utilized to achieve organizational goals, a critical function in ensuring sustainability and competitiveness. Globally, this process has evolved with the integration of advanced tools like artificial intelligence, which enhance the precision and speed of decisions in areas such as budgeting and forecasting (Ahmed et al., 2025). In the context of manufacturing, financial decision-making is complex due to fluctuating costs, market demands, and operational uncertainties, making it a key area for innovation (Ocran et al., 2024). This study examines four specific measures resource allocation, investment planning, cost management, and risk assessment as they represent core components influenced by AI in Nairobi County's manufacturing sector (Ogalloh, 2023). These measures are selected for their direct impact on financial performance and their relevance to the local industrial landscape, where empirical insights are limited.

Resource allocation, the first measure, refers to the process of distributing financial and operational resources, such as capital and labor, across a firm's activities to maximize efficiency and output. In manufacturing, effective resource allocation ensures that production lines are funded adequately while avoiding waste, a challenge in Nairobi's resource-scarce environment (Pinto et al., 2023). AI tools can optimize this process by analyzing demand patterns and operational needs, yet the extent of their influence in Kenyan firms remains unclear (Kakai & Anyieni, 2024). This measure is included because it is foundational to financial stability and its enhancement through AI could address local

constraints, justifying further investigation (Mwangi, 2024). Understanding its dynamics will reveal how technology supports resource efficiency in this context.

Investment planning, the second measure, involves deciding where and how to invest capital, such as in new machinery or market expansion, to ensure long-term growth and profitability in manufacturing firms. This process requires balancing short-term costs with future returns, a task complicated by Nairobi's economic volatility and limited access to financing (Chege, 2024). AI-driven insights, such as those from predictive analytics, could improve investment decisions by forecasting returns, but their application in this setting lacks documentation (Addy et al., 2024). Its selection is warranted by its critical role in firm expansion and the potential for AI to refine planning, making it a vital area for study (Eng'airo, 2024). Exploring this measure will clarify how technology aids strategic financial growth locally.

Cost management, the third measure, entails controlling and reducing expenses related to production, labor, and overheads to maintain profitability, a pressing concern for Nairobi's manufacturers facing rising operational costs. Effective cost management ensures competitiveness by identifying inefficiencies and optimizing spending, areas where AI automation could play a transformative role (Ononiwu et al., 2024). Despite its importance, there is little evidence on how AI influences cost management practices in Kenyan manufacturing, highlighting a research gap (Mwangi, 2024). This measure is chosen for its direct link to financial health and the promise of AI to streamline cost-related decisions, necessitating empirical analysis (Chege, 2024). Its study will shed light on technology's role in maintaining economic viability.

Risk assessment, the fourth measure, involves evaluating potential financial uncertainties, such as market fluctuations or supply chain disruptions, and devising

strategies to mitigate them in manufacturing operations. In Nairobi, where firms face unpredictable energy costs and global competition, robust risk assessment is essential for financial resilience (Mwangi, 2024). AI tools like machine learning can enhance this process by predicting risks and suggesting mitigation, yet their local impact is underexplored. This measure is included due to its significance in safeguarding financial outcomes and the potential for AI to improve risk management, justifying its examination (Mutitu, 2024). Together, these four measures provide a comprehensive lens to assess how AI shapes financial decision-making in Nairobi County's manufacturing sector.

1.1.3 Manufacturing Firms in Nairobi County, Kenya

Nairobi County is Kenya's principal industrial hub, hosting a diverse set of manufacturers across food processing, textiles, chemicals, and metal products, with the sector contributing roughly a tenth of national output (Kiptum, 2021). The county accommodates well over 500 registered manufacturers, reflecting both long-standing incumbents and newer entrants responding to urban demand and export opportunities (Christopher et al., 2021). This industrial base aligns with national ambitions for structural transformation and competitiveness, positioning the county as central to Kenya's broader development trajectory (Ogalloh, 2023).

Firms span micro, small, and medium enterprises alongside large corporates, creating a layered ecosystem in which supply chains, distribution networks, and labor markets intersect (Christopher et al., 2021). Location advantages—transport infrastructure, proximity to regulators and finance, and access to skilled labor—support operations, though persistent headwinds such as energy costs and financing constraints moderate performance outcomes (Ogalloh, 2023). Recent discussions of operating conditions also highlight demand variability and cost pressures that unevenly affect firms by size and subsector,

contributing to mixed growth signals across the manufacturing base (Mwangi, 2024; Waguthii, 2021; Chege, 2024).

This study focuses on active, registered manufacturers within Nairobi County across major subsectors to capture the county's diversity while maintaining a coherent operating context (Christopher et al., 2021). Nairobi was chosen because its firm concentration allows robust sampling and because finance functions are typically formalized, enabling organization-level insights into decision processes (Ogalloh, 2023; Otuke, 2023). Finance managers were the unit of observation given their direct oversight of reporting, planning, and resource allocation within firms, a choice consistent with prior work examining financial decision environments in Nairobi's industrial setting (Kakai & Anyieni, 2024; Mutitu, 2024; Eng'airo, 2024).

1.2 Statement of the Problem

In an ideal setting, manufacturing firms would make optimal financial decisions using advanced tools to enhance efficiency, profitability, and economic impact. For instance, if Kenyan manufacturing firms effectively utilized financial strategies such as resource allocation, investment planning, cost management, and risk assessment, they could increase production capacity, minimize waste, and enhance competitiveness. This would in turn boost GDP—where manufacturing already contributes approximately 10%—create more jobs for the over 300,000 currently employed in the sector, and increase tax revenues for public services (Kiptum, 2021; Tsuma, 2025). Furthermore, efficient financial decisions would stimulate innovation and export growth, elevating Kenya's role in regional and global trade (Ronoh, 2023). Collectively, these improvements would position Nairobi County as a thriving industrial hub aligned with the Vision 2030 development agenda.

However, the reality on the ground is markedly different. Financial decision-making in Nairobi's manufacturing firms remains largely sub-optimal, limiting firm growth and national economic gains. For example, a 2022 survey reported that 68% of Kenyan manufacturing firms experienced cost management inefficiencies, while those based in Nairobi cited high operational losses due to poor forecasting and inadequate risk assessment (Ononiwu et al., 2024). The sector's growth rate has remained stagnant at 2.3%—well below the Vision 2030 target of 10%—pointing to deeper issues in investment planning and resource utilization (Mutitu, 2024). These inefficiencies result in reduced productivity, job losses, lower GDP contributions, and declining global competitiveness (Addy et al., 2024). Emerging technologies like AI offer promising solutions to these challenges. Tools such as predictive analytics, machine learning, automated financial reporting, and natural language processing can significantly enhance data-driven financial decision-making. However, despite their potential, these technologies remain underutilized, and their impact in the local manufacturing context is largely untested (Mwangi, 2024). Without targeted adoption and evaluation, financial inefficiencies may persist and further undermine the sector's potential.

Empirical literature supports AI's contribution to efficiency in manufacturing, especially in developed countries. However, local studies in Kenya have mostly explored general technology adoption, with limited focus on the specific impact of AI on financial decision-making in manufacturing firms (Eng'airo, 2024). Global findings while encouraging are often derived from contexts with robust infrastructure and advanced digital capabilities, limiting their relevance to emerging markets like Kenya (Ahmed et al., 2025). Moreover, local research has primarily examined AI in sectors such as agriculture, neglecting the manufacturing industry altogether (Koech, 2022). Thus, the research

problem was the lack of empirical evidence on how AI tools influence financial decision-making in manufacturing firms in Nairobi County, Kenya.

1.3 Objectives of the Study

The general objective of this study was to establish the influence of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya.

The specific objectives were:

i. To establish the influence of predictive analytics on financial decision-making in manufacturing firms in Nairobi County, Kenya

ii. To establish the influence of machine learning models on financial decision-making in manufacturing firms in Nairobi County, Kenya

iii. To examine the influence of automated financial reporting on financial decision-making in manufacturing firms in Nairobi County, Kenya

iv. To determine the influence of natural language processing tools on financial decision-making in manufacturing firms in Nairobi County, Kenya.

1.4 Research Hypotheses

The study addressed the following null research hypotheses:

i. **H_{01}:** Predictive analytics have no significant influence on financial decision-making in manufacturing firms in Nairobi County, Kenya

ii. **H_{02}:** Machine learning models have no significant influence on financial decision-making in manufacturing firms in Nairobi County, Kenya

iii. **H_{03}:** Automated financial reporting has no significant influence on financial decision-making in manufacturing firms in Nairobi County, Kenya

iv. **H_{04}:** Natural language processing tools have no significant influence on financial decision-making in manufacturing firms in Nairobi County, Kenya

1.5 Justification of the Study

This study was justified by the urgent need to understand how artificial intelligence can enhance financial decision-making in manufacturing firms in Nairobi County, Kenya, a region where economic growth hinges on industrial performance yet is hampered by inefficiencies. As these firms face challenges like rising costs, limited capital, and market volatility, optimizing resource allocation, investment planning, cost management, and risk assessment is critical to their survival and contribution to the economy. AI tools predictive analytics, machine learning models, automated financial reporting, and natural language processing offer promising solutions to improve accuracy, efficiency, and strategic foresight, yet their practical impact in this specific context remains largely unknown. By exploring this intersection, the study addresses a pressing practical problem while contributing valuable insights to both local manufacturers and policymakers aiming to bolster Kenya's industrial sector. This research is timely and relevant, aligning with national goals to leverage technology for sustainable development, making it a vital step toward unlocking the full potential of Nairobi's manufacturing landscape.

1.6 Significance of the Study

This study is of significance to the following:

1.6.1 Policymakers

This study offers critical insights for policymakers in Kenya, particularly those shaping industrial and technological strategies under Vision 2030. By demonstrating how AI tools like predictive analytics and automated financial reporting enhance financial decision-making in Nairobi County's manufacturing firms, it provides evidence to support policies

promoting AI adoption. This could lead to targeted incentives, such as subsidies or training programs, to bridge the digital divide and boost economic growth. Policymakers can use these findings to strengthen the manufacturing sector's contribution to GDP and employment.

1.6.2 Manufacturing Firms in Nairobi County

For manufacturing firms in Nairobi County, this study delivers practical guidance on leveraging AI to optimize financial decisions, directly addressing challenges like cost management and risk assessment. Managers can adopt tools such as machine learning models to improve investment planning, enhancing competitiveness in a volatile market. The findings will provide a roadmap for integrating AI into daily operations, potentially reducing losses and increasing profitability. This practical relevance empowers firms to align with global trends while tackling local constraints.

1.6.3 Researchers and Academicians

Academically, this study fills a gap in the literature by exploring AI's impact on financial decision-making within an emerging market context, specifically Nairobi's manufacturing sector. It extends theories like the Technology Acceptance Model and Resource-Based View by testing their applicability in a Kenyan setting, enriching scholarly understanding. By providing empirical data from a quantitative approach, it contributes to the limited body of research on AI in African manufacturing. This advances knowledge and sets a foundation for future studies in similar contexts.

1.7 Scope of the Study

The scope of this study encompassed an examination of the influence of artificial intelligence on financial decision-making within manufacturing firms located in Nairobi County, Kenya, focusing on a specific set of AI tools and financial measures. It targets four

AI variables predictive analytics, machine learning models, automated financial reporting, and natural language processing tools and assesses their influence on four financial decision-making aspects: resource allocation, investment planning, cost management, and risk assessment. The study was geographically limited to Nairobi County, the industrial hub of Kenya, and included a sample of 349 registered manufacturing firms of varying sizes, selected through stratified random sampling. It adopted a purely quantitative approach, utilizing primary data collected via structured questionnaires from financial managers, with data analysis involving descriptive and inferential statistics, including regression analysis. The study was conducted between June and September 2025.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive review of existing literature relevant to the study, focusing on the theoretical, empirical, and conceptual foundations that inform the relationship between artificial intelligence and financial decision-making in manufacturing firms.

2.2 Theoretical Review

This study was guided by four key theories that explain the adoption and impact of artificial intelligence in financial decision-making. These are the Technology Acceptance Model (TAM), Resource-Based View (RBV), Automation Theory, and Cognitive Fit Theory, each aligning with a specific AI tool explored in the study.

2.2.1 Technology Acceptance Model

TAM, developed by Davis (1989), is one of the most widely adopted frameworks for understanding how users accept and use technology. The model posits that two key factors—perceived usefulness and perceived ease of use—influence a person's behavioral intention to use a technology, which subsequently affects actual usage (Davis, 1989). Perceived usefulness refers to the extent to which an individual believes that a particular system enhances job performance, while perceived ease of use refers to the degree to which one believes that using the system would be free from effort (Muazu et al., 2024).

Over the years, TAM has been empirically validated in various fields, including healthcare, finance, and education, and is recognized for its parsimonious yet robust structure in explaining technology adoption behaviors (Ejdys, 2024). Despite its widespread application, TAM has received criticism for its simplistic view of technology

adoption. Scholars argue that it does not sufficiently account for organizational, cultural, and social influences that play a significant role in real-world adoption processes (Theoharakis & Mylonopoulos, 2022). Moreover, the model's primary focus on individual-level decision-making fails to reflect collective or managerial dynamics prevalent in enterprise contexts, particularly in sectors such as manufacturing where financial decisions are often made through team-based deliberation (Shaengchart, 2023). These limitations have led to the development of extended models such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates social influence, facilitating conditions, and other constructs to provide a more holistic explanation (de Souza et al., 2023).

In the context of this study, TAM was particularly relevant in examining the adoption of predictive analytics by finance professionals in manufacturing firms within Nairobi County. Predictive analytics tools, which are designed to enhance financial forecasting, budgeting, and risk analysis, must be perceived as both useful and easy to use for them to be accepted (Shishakly et al., 2023). Finance managers are more likely to adopt these tools if they believe the systems will improve the accuracy and speed of financial decision-making. In developing countries where technical skills and resources may be limited, these perceptions are even more influential in determining whether a firm integrates AI tools into its financial workflows. TAM also helps explain why adoption levels vary across firms in the same industry and locality. For instance, larger firms with more access to digital infrastructure and internal technical support may perceive predictive analytics tools as more beneficial and easier to use, increasing the likelihood of adoption. In contrast, smaller firms may view the same tools as complex or burdensome, especially if their usefulness is not well demonstrated or the interface is difficult to navigate. These variances in perception and acceptance underscore the practical applicability of TAM in

understanding the behavioral intentions behind technology use in financial contexts (Raut & Kumar, 2024).

Moreover, applying TAM to predictive analytics adoption provides valuable insights into behavioral drivers that go beyond technological determinism. Studies have shown that the behavioral intention to use technology is not solely a function of system attributes but is also shaped by past experiences, job relevance, and individual confidence in using digital tools (Venkatesh & Davis, 2000; Oliveira et al., 2022). In this regard, perceived ease of use influences perceived usefulness, suggesting that if a system is perceived as effortless, users are more likely to recognize its potential benefits (Dwivedi et al., 2023). This causal linkage is especially important in financial settings where complex systems may deter usage if training and system design are not prioritized.

In addition, the theory supports interventions that can enhance technology adoption by addressing cognitive and motivational barriers. For instance, organizational efforts such as user training, interface simplification, and demonstration of value through pilot programs have been shown to increase both perceived ease of use and perceived usefulness (Cheng & Wang, 2021; Asamoah et al., 2023). In resource-constrained environments like Nairobi's manufacturing sector, low-cost interventions aligned with TAM's constructs can significantly influence the speed and scale of AI adoption. This reinforces the model's managerial relevance, making it not only a diagnostic tool but also a framework for designing actionable strategies to improve technology uptake.

Furthermore, recent advancements in TAM research emphasize its adaptability to emerging technologies such as AI, machine learning, and predictive analytics. Scholars have proposed augmented TAM models that integrate constructs such as trust, system transparency, and AI explainability to address newer adoption concerns (Jussupova & Ahn,

2022; Al-Gahtani et al., 2023). These adaptations make TAM more suitable for AI-related research, where black-box systems can raise skepticism among users unless the system is perceived as trustworthy and easy to interpret. In this light, TAM continues to evolve, demonstrating its robustness in exploring complex digital transformations across industries.

Finally, applying TAM in this study contributes to expanding its relevance in emerging market contexts, where little empirical work has been done. Most TAM-based research focuses on developed economies; thus, using it to understand the dynamics of AI adoption in Kenyan manufacturing firms enhances the model's external validity. In doing so, this study not only leverages TAM as a theoretical framework but also provides practical insights into how user perceptions shape the adoption of predictive analytics. It supports the hypothesis that perceived usefulness and ease of use are critical drivers in the integration of AI tools into financial decision-making processes in Nairobi's manufacturing sector.

2.2.2 Resource-Based View Theory

The Resource-Based View (RBV), introduced by Barney (1991), is a strategic management theory that explains how firms gain and maintain competitive advantage through the acquisition and strategic use of internal resources. According to the theory, for a resource to contribute to sustained competitive advantage, it must possess four critical attributes: it must be valuable, rare, inimitable, and non-substitutable—commonly referred to as the VRIN criteria (Coşkun & Öztürk, 2024). The RBV shifts the focus of firm performance from external market conditions to the internal capabilities and assets that firms control, asserting that competitive advantage stems not just from owning resources but from how these resources are deployed and managed (Wernerfelt, 1984; Balcıoğlu, 2025). In modern contexts, intangible assets such as technological capabilities, knowledge, and AI tools like

machine learning models are increasingly recognized as strategic resources under RBV (Liu et al., 2021; Wamba et al., 2021).

While RBV provides a compelling framework for analyzing internal sources of competitive advantage, it has been criticized for several limitations. One of the key critiques is that RBV tends to view resources as static, offering little guidance on how they are acquired, renewed, or integrated into dynamic operational environments (Akram & Abrar Ul Haq, 2022). Additionally, RBV has been faulted for underemphasizing the external environment, such as market turbulence, technological change, and institutional constraints, which often influence how resources are developed and utilized (Wibisono & Supoyo, 2023). Furthermore, the theory has been seen as vague in defining what constitutes a resource, leading to inconsistencies in its application across empirical studies (Ozturk, 2021). In response, scholars have extended RBV by integrating it with the dynamic capabilities framework, which emphasizes the firm's ability to adapt, reconfigure, and innovate in response to changing conditions (Balcıoğlu, 2025).

In applying RBV to this study, machine learning models are conceptualized as intangible, knowledge-based assets that can provide financial decision-making advantages when integrated into firm operations. These models, when uniquely tailored to an organization’s data infrastructure and workflows, meet the VRIN criteria by enabling predictive accuracy, speed of analysis, and responsiveness to complex financial scenarios—capabilities that are difficult for competitors to replicate (Paramesha et al., 2024; Dhamija et al., 2023). When properly aligned with strategic decision-making, such tools enhance internal competencies, reduce reliance on external financial consultants, and enable more autonomous financial planning and investment decisions, particularly within dynamic environments like manufacturing.

Moreover, RBV supports the argument that sustainable competitive advantage in financial decision-making arises not merely from possessing technology, but from how well it is embedded in organizational routines, staff expertise, and decision-support systems (Agyapong et al., 2022; Arora & Sharma, 2021). For instance, machine learning tools trained on firm-specific financial data develop nuanced patterns unique to the organization, creating an analytics ecosystem that is not easily transferrable. These tools, when supported by internal training, feedback loops, and knowledge-sharing systems, form part of a broader capability set that generates superior decision-making over time, consistent with RBV's emphasis on internal strategic resources.

Furthermore, empirical studies have shown that firms in emerging economies can harness the RBV by investing in context-relevant technological resources that are difficult to imitate due to localized customization (Nguyen et al., 2022; Musau & Nyongesa, 2023). In Nairobi's manufacturing sector, firms that effectively integrate machine learning into budgeting, cost control, and financial forecasting are more likely to achieve superior financial agility, especially under fluctuating economic conditions. Such integration creates a knowledge-intensive decision infrastructure that enhances firm performance, aligning with the RBV's proposition that internal competencies yield enduring advantages when they are hard to replicate and evolve over time.

In the context of this study, the RBV was applicable in assessing how machine learning models function as strategic resources within manufacturing firms to enhance financial decision-making. Machine learning tools enable firms to analyze large volumes of historical and real-time financial data, uncover patterns, forecast trends, and make informed investment decisions—all of which align with the VRIN attributes when these capabilities are well-developed and uniquely applied (Paramesha et al., 2024). According

to RBV, firms that effectively deploy such advanced analytical capabilities are more likely to outperform their competitors by achieving better financial planning, risk management, and resource optimization (Abrokwah-Larbi, 2024). Therefore, the theory provides a basis for hypothesizing that machine learning models positively influence financial decision-making outcomes, particularly in firms that treat these technologies as core, inimitable, and value-creating resources.

2.2.3 Automation Theory

Automation Theory has its roots in the foundational work of Wiener (1948), whose research in cybernetics introduced the concept of feedback mechanisms in machine control systems. The theory posits that tasks historically executed by humans can be transferred to machines through automation, resulting in increased productivity, consistency, and operational efficiency (Johnson et al., 2021). Over time, Automation Theory has evolved to encompass a wide range of organizational applications, including the digitization of business functions such as manufacturing, logistics, human resources, and financial reporting. It emphasizes that machines can be programmed to perform routine, repetitive tasks, thereby reducing the burden on human workers and improving overall system reliability (Chang-Yin et al., 2021).

In modern organizational contexts, Automation Theory is frequently applied to explain how firms adopt technological systems to enhance efficiency and decision-making accuracy. Automation tools, including enterprise resource planning (ERP) systems and AI-driven reporting software, are increasingly integrated into core business operations to streamline processes and reduce the likelihood of human error (Choudhuri, 2024). In the domain of financial management, automation enables real-time reporting, automated reconciliation, and regulatory compliance—all of which support faster and more precise

financial decisions. As such, the theory underpins the rationale for replacing manual, paper-based processes with digital systems to support data consistency and timely access to critical financial insights (Otuke, 2023).

Despite its practical appeal, Automation Theory has been criticized for adopting an overly technical and deterministic perspective. It tends to assume that automation will always lead to positive outcomes, often neglecting the social and organizational challenges that may accompany technological transitions (Daylami, 2024). Key concerns include job displacement, skill mismatches, and employee resistance to change—issues that are particularly salient in developing economies where digital literacy levels vary widely. Additionally, automation initiatives may face operational barriers such as the high cost of implementation, system incompatibility, and limited training, which are not adequately addressed by the theory's traditional framework (Srai & Christodoulou, 2020).

Another important critique is that Automation Theory often underestimates the complexity of socio-technical systems, where human and technological components interact in dynamic ways. Scholars argue that effective automation requires more than just technical feasibility; it demands organizational readiness, cultural alignment, and leadership support (Zarei et al., 2024). In sectors such as manufacturing, where decision-making processes are multifaceted and data-driven, over-reliance on automation without appropriate human oversight can introduce new risks—especially in financial reporting, where contextual judgment, regulatory interpretation, and ethical considerations are critical (Kaggwa et al., 2024).

Moreover, automation does not operate in isolation but must be integrated within a firm's broader information systems architecture. Studies have shown that the success of financial automation depends heavily on interoperability with legacy systems, user

interface design, and ongoing maintenance and support structures (Mutiso & Ochieng, 2023; Muthoni & Githinji, 2022). As manufacturing firms modernize their operations, the gradual rollout of automation rather than complete system overhaul is often recommended to manage risk and foster user acceptance. This incremental approach aligns with Automation Theory's evolution, highlighting that automation is not a one-time event but a continuous process influenced by organizational learning and technological adaptation.

Additionally, automation in financial reporting enhances real-time visibility into key metrics, enabling finance managers to make swift, data-driven decisions (Kakai & Anyieni, 2024; Choudhuri, 2024). For example, automation tools can auto-generate dashboards that visualize key performance indicators (KPIs), cash flow trends, and budget variances—tools that not only save time but also enhance financial foresight. This proactive decision-making capability is particularly valuable in manufacturing environments characterized by high volumes, tight margins, and complex supply chains, where timely financial insights are critical to operational success (Biswas et al., 2024; Otuke, 2023).

Nonetheless, the realization of automation benefits is contingent upon firm-level factors such as technological readiness, managerial commitment, and employee competence (Mwangi & Mugambi, 2022). In the Kenyan context, disparities in digital infrastructure and technical expertise mean that not all manufacturing firms are equally poised to leverage automation. Automation Theory, when applied in such settings, must therefore be viewed through a contextual lens that accounts for capacity-building, policy incentives, and phased implementation. These factors can influence the extent to which automated financial reporting translates into improved financial decision-making outcomes (Kaggwa et al., 2024; Zarei et al., 2024).

In the context of this study, Automation Theory supports the hypothesis that automated financial reporting positively influences financial decision-making in manufacturing firms in Nairobi County. The theory predicts that firms leveraging automation in their reporting processes are better positioned to make timely and data-driven financial decisions due to increased efficiency and accuracy (Biswas et al., 2024). As manufacturing firms in Kenya increasingly face cost pressures and regulatory demands, automation offers a practical solution to streamline financial workflows and reduce operational friction. This research applies Automation Theory to explore how such digital systems can transform financial reporting practices and enhance decision quality, especially in resource-constrained settings where operational efficiency is vital for competitiveness.

2.2.4 Cognitive Fit Theory

The Cognitive Fit Theory (CFT), developed by Vessey (1991), seeks to explain how the alignment or "fit" between the format of information presentation and the nature of a task affects user performance and decision accuracy. The theory posits that when the method of presenting information matches the cognitive processes required to perform a task, individuals can process information more effectively, resulting in improved outcomes (Janson & Dickhäuser, 2025). CFT is grounded in cognitive psychology and emphasizes that task performance is enhanced when there is congruence between a user's mental representation of the task and the information display. This alignment reduces cognitive load, improves speed, and supports more confident decision-making (Sharma et al., 2025).

In the domain of information systems and technology, CFT has been widely applied to examine how data visualization, dashboards, and user interfaces affect decision-making efficiency. For instance, graphical formats are often more suitable for spatial or comparative tasks, while tabular formats are better for retrieving precise numeric data

(Martínez-Molés et al., 2024). CFT has also been instrumental in interface design, where mismatches between the task structure and data representation can lead to poor comprehension and decision errors. In decision-support systems, ensuring that the format of financial or operational data fits the mental model of the user enhances task performance, particularly in time-sensitive or high-stakes environments (Zhang et al., 2022).

Despite its utility, CFT has been criticized for several limitations. One of the primary concerns is its restricted generalizability most empirical validations have been conducted in controlled environments using simple tasks, limiting the theory's applicability to complex, real-world decisions such as strategic financial planning (Mandelburger & Mendling, 2021). Additionally, the theory often overlooks individual differences, such as expertise, prior knowledge, and learning styles, all of which can affect how users interact with data formats and interpret outputs (Almuqrin & Mutambik, 2021). Another critique is that CFT does not fully consider how technology-mediated environments are evolving, particularly with the rise of AI-powered tools that present data in new forms like voice, sentiment, and natural language summaries.

Recent advancements in artificial intelligence and natural language processing (NLP) have created new opportunities and challenges for applying CFT. Unlike traditional information formats, NLP tools convert large volumes of unstructured text into structured outputs such as summaries, sentiment scores, and predictive insights (Mutitu, 2024). This evolution raises questions about how well these outputs fit the mental frameworks of users, especially in tasks that require quick synthesis of multiple data sources. While NLP tools can enhance information access, their effectiveness depends on how intuitively the results are presented to match the decision-makers' expectations and cognitive preferences (Abdelhamid et al., 2021).

Moreover, scholars argue that the true value of CFT in the digital age lies in its potential to guide the design of intelligent interfaces that integrate visual, textual, and predictive data elements (Gupta & Mukherjee, 2023). For example, financial dashboards that combine NLP-generated text summaries with interactive graphs and risk heat maps may better align with the decision tasks faced by finance professionals. This blended format supports users in scanning, filtering, and interpreting complex datasets more efficiently, especially in resource-constrained or time-sensitive environments (Sharma et al., 2025; Zhang et al., 2022). By applying CFT principles, developers can ensure that AI-enabled tools are not only technically robust but also cognitively usable.

Additionally, the relevance of CFT is heightened in cross-cultural and emerging market contexts where familiarity with digital tools may vary significantly among users. In Kenya's manufacturing sector, where firms range from technologically advanced multinationals to SMEs with limited digital literacy, the cognitive fit between NLP outputs and decision-makers' mental models become particularly critical (Mutitu, 2024; Okoth & Ombongi, 2023). Poorly designed systems may confuse rather than aid users, reducing the efficacy of AI tools and undermining adoption. Thus, CFT offers practical insights for ensuring inclusivity and usability in technology deployment across diverse organizational settings.

In the context of this study, Cognitive Fit Theory provides a critical lens for analyzing how NLP tools affect financial decision-making within manufacturing firms in Nairobi County. Financial managers often need to interpret vast amounts of unstructured data such as reports, contracts, and market feedback within short timeframes. NLP tools can streamline this process, but only if the output formats (visualizations, summaries, or dashboards) are cognitively aligned with the specific nature of the financial decision at

hand (Sharma et al., 2021). For instance, when evaluating financial risks or investment options, NLP outputs that are clearly structured and contextually relevant are likely to enhance decision accuracy and reduce the cognitive effort required.

Therefore, the application of CFT in this study supports the hypothesis that NLP tools significantly influence financial decision-making by improving cognitive alignment between financial information and the task structure. This alignment not only improves processing efficiency but also contributes to more confident and timely decisions in environments characterized by data overload and limited processing time (Lotfi et al., 2023). As financial environments become increasingly digitized and AI-driven, the relevance of CFT is heightened, particularly in emerging markets where firms are just beginning to adopt advanced decision-support technologies. Thus, CFT reinforces the importance of user-centered design in the deployment of NLP tools, ensuring that the technology supports rather than complicates financial decision-making.

2.3 Empirical Review

This section examined previous research conducted by other academicians on how artificial intelligence influences financial decision-making globally, regionally, and locally and presents the existing research gaps.

2.3.1 Predictive Analytics and Financial Decision-Making

Empirical studies show growing interest in predictive analytics as a decision-enhancing tool across industries, though its application varies significantly across sectors and regions. In the financial services sector, predictive analytics has been extensively studied for its role in improving forecasting and strategic planning. For example, Olagoke (2025) found that predictive analytics significantly improved financial forecasts and risk mitigation in Nigerian banks. However, such sector-specific insights are limited in transferability to

manufacturing contexts, where cost structures, decision cycles, and investment horizons differ. Similarly, Kelvin and Morrisson (2023) explored predictive analytics within Nairobi's healthcare industry, showing improvements in service optimization and strategic foresight, but their findings cannot directly inform manufacturing firms due to differing financial structures and regulatory environments.

In the manufacturing sector globally, predictive analytics has been associated with enhanced investment and risk decisions. Hossain et al. (2024) and Zong and Guan (2024), studying Pakistani and Chinese manufacturing firms respectively, noted that firms using AI-based forecasting tools were more effective in investment planning and credit risk management. However, both studies focused on large firms in relatively mature digital environments and largely excluded SMEs or unlisted entities. Lee et al. (2022) similarly demonstrated how Malaysian manufacturers leveraged predictive analytics for better budgeting and cash flow forecasting. These studies underscore predictive analytics' potential but tend to assume high levels of data availability, infrastructure, and technical expertise—conditions not universally present in developing countries like Kenya.

Regionally, studies on East African manufacturing firms remain sparse and methodologically limited. Maganga and Taifa (2023) reported that predictive analytics improved risk management among East African conglomerates, but their reliance on secondary data limits insight into behavioral and process-level mechanisms. Mogaka (2023), in a Kenyan food processing context, linked predictive analytics to procurement efficiency but did not assess its direct impact on financial decision-making variables such as investment or cost planning. Moreover, most local studies, including those by Mogaka and Kelvin & Morrisson, focus either on operational efficiency or performance outcomes,

rather than on how predictive analytics shapes decision-making behavior itself—a critical conceptual gap.

Across these studies, methodological limitations are also apparent. Several papers (e.g., Maganga & Taifa, 2023; Odesanya & Odigie, 2022) depend on descriptive designs or secondary data, offering limited causal insights. Others (e.g., Zong & Guan, 2024) employ robust statistical models like SEM but only within large-cap, exchange-listed firms. Consequently, findings are not representative of the diverse firm sizes and technology adoption levels typical of Nairobi's manufacturing sector. There is also a lack of context-specific theoretical grounding, with most studies not integrating frameworks like the Technology Acceptance Model or Decision Theory to explain how predictive analytics affects managerial judgment, confidence, or accuracy.

In synthesis, while existing literature affirms the relevance of predictive analytics in enhancing budgeting, forecasting, and risk assessment, it largely fails to unpack how and under what conditions these tools influence financial decision-making. Studies from developed economies highlight technical capabilities but often overlook the cognitive and organizational dynamics at play in emerging markets. Few studies have examined interaction effects of predictive analytics on financial outcomes. The lack of studies anchored in behavioral or decision-making theory also limits our understanding of adoption and use patterns in low-automation contexts.

Therefore, the current study addresses a critical conceptual and contextual gap by investigating how predictive analytics influences financial decision-making specifically budgeting, investment planning, cost management, and risk assessment within Nairobi's manufacturing sector. By drawing on the Technology Acceptance Model and collecting

primary data from finance managers, it seeks to uncover both behavioral drivers and financial outcomes, contributing to theory and practice alike.

H_{01}: Predictive analytics has no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya.

2.3.2 Machine Learning Models and Financial Decision-Making

The application of machine learning in financial decision-making has gained traction globally, with studies showing that these tools can significantly enhance forecasting, budgeting, investment planning, and risk assessment. However, the literature remains fragmented across industries and contexts, with notable gaps in conceptual integration and emerging economy perspectives.

In developed and industrialized economies, machine learning is widely recognized for improving financial forecasting and capital planning. Nguyen (2024), studying Vietnamese corporate finance systems, found that ML enhanced capital allocation and return on investment through optimized budgeting and portfolio modeling. Similarly, Wasserbacher and Spindler (2022) noted the increasing sophistication of ML algorithms in automating financial models and detecting anomalies. Despite these contributions, most studies in this category are theoretical or rely heavily on secondary data from listed firms, with minimal focus on managerial interpretation or internal decision dynamics. This reflects a conceptual gap—few studies explore *how* ML shapes decision-making behavior, not just performance outcomes.

In contrast, studies in emerging markets tend to focus on operational or peripheral aspects of ML. For instance, Hossain et al. (2025) examined ML's role in budget execution in Bangladeshi industrial firms, reporting reductions in expenditure variance. However, the study relied solely on system-generated reports and did not assess how financial managers

interact with or interpret ML-generated outputs—a critical omission for understanding cognitive and behavioral impacts. Similarly, Ashtiani and Raahemi (2021) focused on fraud detection in Indian manufacturing firms, offering useful insights into anomaly detection but not broader strategic financial decisions such as investment planning or resource optimization.

In the African context, empirical work on ML's financial applications is scarce and often lacks sectoral depth. Arakpogun et al. (2021) found that ML improved decision accuracy across various business functions in African enterprises but did not isolate financial decisions as a focus area. Masila (2023) highlighted the benefits of big data capabilities—including ML—on profitability and cost control in listed Kenyan manufacturing firms. However, the study emphasized financial performance rather than exploring specific decision-making processes like capital budgeting, risk evaluation, or resource allocation. These studies reveal an empirical gap: limited exploration of ML's role in internal financial strategy formulation, especially within unlisted or small-to-medium firms common in Nairobi.

Kenya-specific studies further underscore these gaps. Macharia (2023) investigated ML in tech-oriented Nairobi firms, identifying improvements in real-time monitoring and analytics. Yet, the study's scope was confined to startups, overlooking traditional manufacturers who face distinct challenges such as legacy systems and limited digital literacy. Mwangi (2024) analyzed ML in supply chain optimization and found enhanced logistics and forecasting accuracy, but the emphasis was on operational rather than financial decision contexts. This pattern illustrates a contextual gap—local studies have not holistically examined how ML supports strategic financial decision-making in manufacturing.

Beyond empirical limitations, a theoretical gap also persists. Most studies do not frame their inquiry within decision-making or adoption theories, such as the Resource-Based View or Technology Acceptance Model. This undermines the understanding of how ML adoption is influenced by internal firm capabilities, perceived usefulness, or managerial experience—key constructs in understanding ML's effectiveness in decision environments.

Collectively, these studies suggest that while ML holds promise for improving financial decisions, few have investigated its strategic application within manufacturing firms in resource-constrained environments. Existing work often generalizes findings, omits behavioral dimensions, or focuses on end outcomes rather than the decision-making process itself.

The current study seeks to address these conceptual, contextual, and theoretical gaps by investigating how ML models influence financial decision-making specifically in budgeting, investment planning, cost management, and risk assessment in Nairobi County's manufacturing firms. Grounded in the Resource-Based View, it treats ML tools not only as technical inputs but as intangible assets that can drive sustained decision-making advantage when effectively embedded into firm processes.

H_{02}: Machine learning models have no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya.

2.3.3 Automated Financial Reporting and Financial Decision-Making

Automated financial reporting has been widely explored for its role in improving efficiency, accuracy, and compliance. However, its direct impact on strategic financial decision-making remains under-researched, particularly in manufacturing contexts within emerging markets. The existing literature spans across public administration, banking, and

production sectors, yet tends to emphasize compliance or performance metrics rather than decision-making behavior.

In developed contexts, Alao et al. (2024) investigated the influence of automation on budget control and capital planning in U.S. corporations. Their findings emphasized error reduction, faster reporting timelines, and improved compliance. However, the study was largely theoretical and did not empirically evaluate how automation affects actual financial decisions such as cost management or investment planning. Similarly, Wang et al. (2024) analyzed robotic automation in manufacturing and found that it improved product-related decisions, but their focus was on production rather than financial decision-making. These studies, while affirming automation's efficiency benefits, reflect a conceptual gap—they do not explain *how* automation shapes the strategic use of financial information in decision-making.

In Kenya, a growing body of literature explores automation within government and financial sectors. For example, Barngetuny (2024) assessed the role of automation in enhancing workflow efficiency within Kenya's Ministry of Finance. While the study highlighted faster data retrieval and reduced bottlenecks, it did not connect these efficiencies to the quality or scope of financial decision-making. Ibrahim (2022) similarly documented automation benefits in IFRS 9 modeling among banks, noting improved compliance and reporting speed. However, these findings are limited to regulatory reporting, neglecting internal financial decisions such as budgeting or capital allocation.

Sector-specific studies in manufacturing offer more relevant insights but remain narrow in scope. Mohammed (2022) reported that automated reporting systems in Kenyan manufacturing firms improved budgeting accuracy and speed. Wekesa (2022) found that pharmaceutical firms enhanced regulatory compliance and audit readiness through

automation. While these findings are promising, both studies focused either on a single financial function (budgeting or compliance) or a niche manufacturing sub-sector, thus revealing an empirical gap in understanding how automation influences the full spectrum of financial decision-making.

Several studies have also explored enterprise-level systems such as ERP platforms. Jayeola et al. (2022), for instance, demonstrated that top management support amplified ERP system impact on financial performance, particularly through improved planning and reporting. However, the study prioritized leadership dynamics and organizational outcomes, with minimal attention to individual-level financial decision processes. Likewise, Lekorere (2022) found that automated accounting systems improved compliance and decision speed in Kenyan banks, but the generalizability of these results to manufacturing is limited due to differences in financial structures, reporting requirements, and operational complexity.

Masila's (2023) findings on big data and real-time analytics in listed manufacturing firms support the potential of automation in enhancing profitability and strategic decision-making. However, the study did not isolate the role of automated financial reporting as a distinct tool influencing resource allocation or risk evaluation decisions. Moreover, few of these studies adopt a behavioral or cognitive lens to understand how finance professionals interact with automated reports—a critical omission in light of the Cognitive Fit Theory, which suggests that the structure and presentation of financial data affects decision accuracy and cognitive load.

In synthesis, existing studies consistently associate automated reporting with improved accuracy, transparency, and compliance. However, few go beyond these operational metrics to investigate how automated systems influence strategic financial

decisions, especially in contexts characterized by limited resources, uneven digital literacy, and rapidly evolving regulatory environments. Moreover, there is little empirical work capturing the perceptions of finance professionals—those most directly responsible for interpreting and acting upon automated financial outputs.

The current study addresses these conceptual, contextual, and theoretical gaps by examining how automated financial reporting influences budgeting, investment planning, cost management, and risk assessment among manufacturing firms in Nairobi County**.** By collecting primary data from finance managers and applying the lens of Automation Theory, the study contributes to a deeper understanding of how automation enhances not just compliance and speed, but the actual quality of financial decisions in a data-driven environment.

H_{03}: Automated financial reporting has no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya.

2.3.4 Natural Language Processing Tools and Financial Decision-Making

Natural language processing a subfield of artificial intelligence has emerged as a transformative tool in organizational decision-making. Although extensively studied in communication, health, and regulatory reporting, its role in enhancing internal financial decision-making remains underexplored, particularly in manufacturing contexts within emerging economies.

In broader AI and analytics literature, NLP is frequently mentioned alongside predictive and machine learning tools, but seldom isolated for financial decision-making analysis. For instance, Ahmed et al. (2025) highlighted how AI technologies including NLP support business analytics through predictive accuracy and operational efficiency. However, the study offered a general overview without delving into NLP's specific role in

shaping financial insights, strategic planning, or decision behavior. Similarly, Chatterjee et al. (2022) investigated factors influencing NLP and big data adoption but did not assess its effect on financial choices, revealing a conceptual gap between adoption determinants and actual decision outcomes.

In sector-specific applications, NLP has shown potential in enhancing reporting and data interpretation. Oyewole et al. (2024) reviewed its use in automating financial reporting, noting improvements in speed, accuracy, and regulatory compliance. However, the study emphasized external reporting functions, leaving out how NLP impacts internal financial decision processes, such as budgeting or risk analysis. Likewise, Anton et al. (2024) explored chatbots in Romanian accounting firms and reported gains in stakeholder communication and data accessibility. Yet, the focus remained on integrated reporting, not financial judgment or strategy formation.

Health and operational sectors have provided more direct examples of NLP's functionality. Hu et al. (2025) conducted a scoping review on NLP applications in African public health, showing how it improves data extraction, sentiment analysis, and reporting from unstructured sources. Chimeudeonwo (2023) explored NLP in electric vehicle manufacturing, finding it useful in streamlining production operations. Although these studies demonstrated the technical versatility of NLP, they lacked application to financial decision contexts, such as cost control, investment planning, or capital allocation.

In the Kenyan context, relevant studies remain limited in both scope and depth. Ndegwa (2024) investigated the readability of financial statements and its effect on stakeholder trust but focused on structural disclosures rather than the application of NLP tools in managerial decision-making. Guo and Polak (2024) discussed enterprise intelligence and financial centralization but did not isolate NLP's role or measure its impact

on firm-level decisions. These gaps indicate a lack of empirical studies linking NLP to behavioral and cognitive aspects of financial decision-making—particularly in high-stakes, data-intensive environments like manufacturing.

Moreover, most prior research has treated NLP primarily as a compliance or reporting facilitator, overlooking its capacity to extract insights from unstructured financial texts (e.g., contracts, audit reports, supplier agreements) and support real-time financial judgment. This represents a missed opportunity to explore how NLP aligns with the Cognitive Fit Theory, which posits that decision accuracy improves when information format matches the task structure. Very few studies evaluate whether NLP tools improve the interpretability of financial information, reduce cognitive load, or increase speed and confidence in decision-making under uncertainty.

Methodologically, many studies reviewed were conceptual, descriptive, or system-based reviews (e.g., Hu et al., 2025; Oyewole et al., 2024), with minimal engagement from actual decision-makers. As such, they lack practical insights into how finance professionals interact with NLP tools, how they interpret NLP-generated summaries, or how these tools influence budgeting, cost management, and risk evaluation in practice. This reflects an empirical gap, especially in emerging markets where digital adoption varies significantly across firm size and sector.

In synthesis, although NLP has demonstrated operational value in data processing and reporting automation, its strategic role in internal financial decision-making—especially in manufacturing firms within resource-constrained environments—remains underexplored. There is limited understanding of its behavioral impact, adoption challenges, and effectiveness in dynamic financial environments.

The current study addresses these empirical, conceptual, and theoretical gaps by investigating how NLP tools influence budgeting, investment planning, cost management, and risk assessment among manufacturing firms in Nairobi County. Anchored on the Cognitive Fit Theory, the study offers new insights into how NLP tools enhance (or hinder) decision alignment, data comprehension, and strategic action in finance departments, contributing to both the AI and financial management literature.

H_{04}: Natural language processing tools have no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya.

2.4 Summary of Literature Review and Research Gaps

The reviewed literature affirms that artificial intelligence tools—such as predictive analytics, machine learning models, automated financial reporting, and natural language processing—can significantly improve various aspects of financial decision-making. Empirical studies across different regions and sectors show that predictive analytics enhances budgeting accuracy and risk forecasting, while machine learning models improve investment planning and anomaly detection. Similarly, automated financial reporting has been shown to reduce errors and improve the timeliness of financial insights, whereas NLP tools facilitate better understanding and interpretation of financial data through real-time textual analysis. The theoretical foundations, including the Technology Acceptance Model, Resource-Based View, Automation Theory, and Cognitive Fit Theory, provide a strong basis for understanding the mechanisms through which these AI tools influence decision-making processes.

Despite these findings, several research gaps persist. First, most prior studies have focused on developed economies or large multinational corporations, leaving a contextual gap in understanding how AI tools affect financial decision-making in emerging economies

like Kenya. Second, many studies have addressed AI adoption broadly or in operational functions, without isolating its effect on specific financial decision-making areas such as resource allocation, cost management, investment planning, and risk assessment. Third, previous studies have often relied on qualitative approaches or limited sample sizes, raising questions about the generalizability of their findings. Additionally, some focused only on one or two AI tools, failing to capture the comprehensive impact of the four key tools examined in this study.

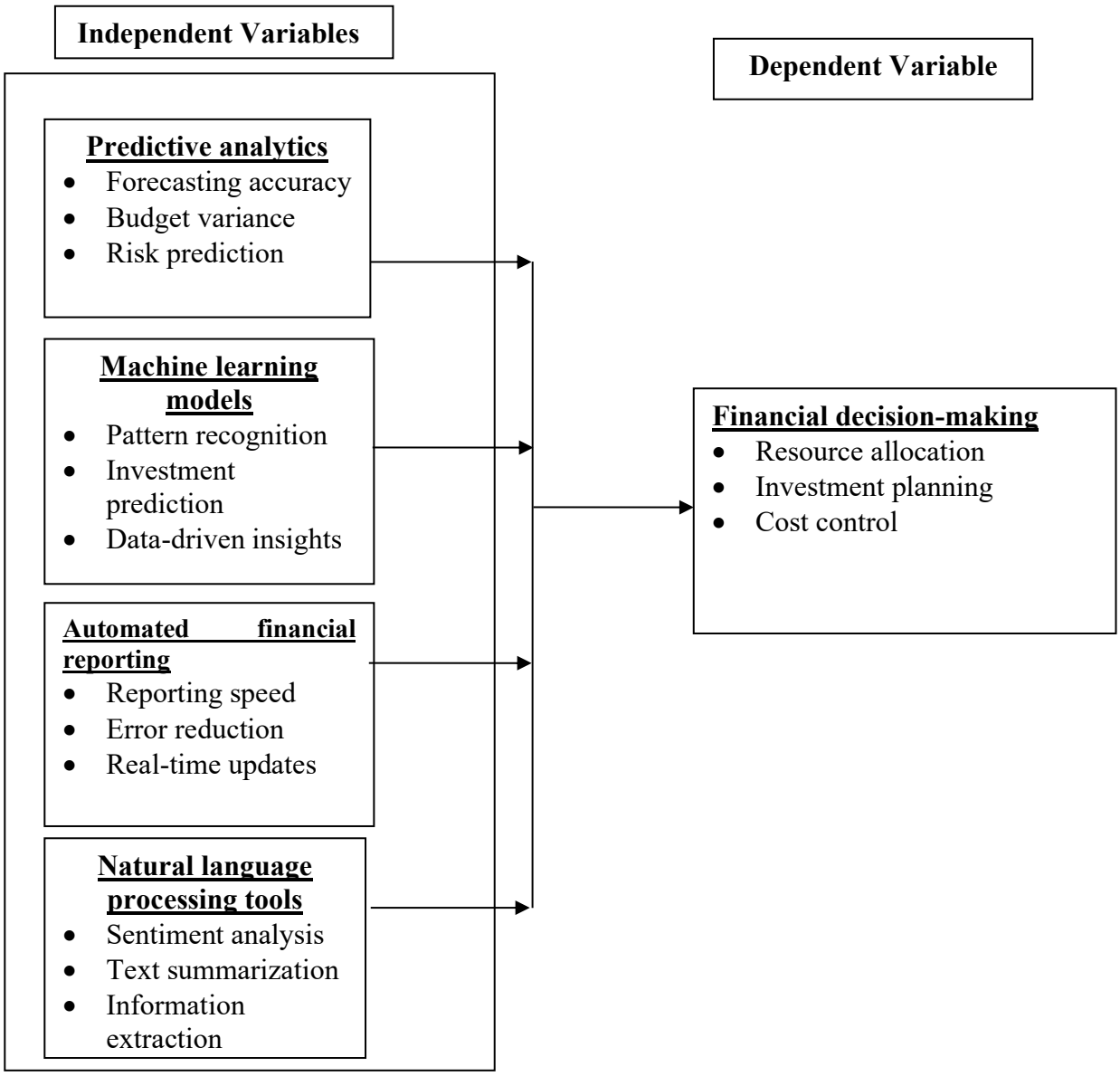
This study sought to address these gaps by focusing on manufacturing firms in Nairobi County, Kenya—a critical yet underexplored context. By assessing the distinct and combined effects of predictive analytics, machine learning models, automated financial reporting, and NLP tools, the study offers a holistic view that advances both academic understanding and practical application in the Kenyan manufacturing sector.

2.5 Conceptual Framework

The conceptual framework for this study illustrates the hypothesized relationships between artificial intelligence technologies and financial decision-making in manufacturing firms within Nairobi County. It serves as a visual and theoretical guide that connects the study's independent variables—predictive analytics tools, automated financial reporting systems, and natural language processing tools—to the dependent variable, financial decision-making. The conceptual framework for this study is as shown in Figure 2.1

FIGURE 2.1:

Conceptual Framework



2.6 Operationalization of Variables

TABLE 2.1:

Operationalization of Variables

Variable type	Variable	Indicators	Measurement scales
Dependent	Financial decision-making	• Resource allocation • Investment planning • Cost control	Likert/ordinal
Independent	Predictive analytics	• Forecasting accuracy • Budget variance • Risk prediction	Likert/ordinal
Independent	Machine learning models	• Pattern recognition • Investment prediction • Data-driven insights	Likert/ordinal
Independent	Automated financial reporting	• Reporting speed • Error reduction • Real-time updates	Likert/ordinal
Independent	Natural language processing tools	• Sentiment analysis • Text summarization • Information extraction	Likert/ordinal

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research design, target population, sampling procedures, data collection methods, and analytical techniques used to examine the effect of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya. It also details the ethical considerations and validity and reliability measures adopted to ensure the integrity of the research process.

3.2 Research Design

This study adopted a descriptive cross-sectional survey design to examine the effect of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya. A descriptive design was appropriate as it enabled the researcher to systematically describe the current state of AI adoption and its anticipated relationship with financial decision-making variables without manipulating any conditions. The cross-sectional approach allowed data to be collected at a single point in time from a broad sample, making it possible to identify patterns and relationships across firms. According to Cooper and Schindler (2021), descriptive research is suitable when the objective is to develop accurate profiles of events, situations, or populations, which aligns with the aim of this proposed study. This design was also preferred for its practicality, efficiency, and potential to yield generalizable insights.

3.3 Target Population

The target population refers to the complete group of individuals or entities that share common characteristics relevant to a particular study (Kothari, 2020). In this study, the target population consisted of the 2,752 active manufacturing firms located in Nairobi

County, Kenya, as recorded by the Nairobi County Government (2024). The focus was on firms that are currently operational, excluding those that are inactive or dormant. These manufacturing firms are categorized into three key sectors: agro-processing, textiles, and light manufacturing, as shown in Table 3.1 below.

TABLE 3.1:

Target Population

Sector	Population
Agro-Processing	857
Textiles	691
Light Manufacturing	1204
TOTAL	**2752**

Source: Nairobi County Government (2024)

3.4 Sample Size and Sampling Procedure

Sampling is the process of selecting a portion of individuals or units from a larger population to represent the whole group. The method used to identify and select these individuals or units is referred to as the sampling technique. A sample size, in this context, refers to a selected subset drawn from the overall population, which serves as the basis for making inferences about the entire group (Cooper & Schindler, 2021). Since the target population for this study was less than 10,000, the Yamane formula, as outlined by Kothari (2020), was used to determine the appropriate sample size. The formula was expressed as:

$$n = \frac{N}{1 + Ne^2}$$

Where n is the desired sample size (if the population is less than 10,000)

N = 2752 at 5% levels of significance.

e=is the precision or sample error i.e.,0.05

$$n = \frac{2752}{1 + 2752(0.05)^2} = 349$$

The study adopted a combination of stratified random sampling and simple random sampling techniques to select the 349 firms. First, stratified sampling was used to group the manufacturing firms into three sectors—agro-processing, textiles, and light manufacturing—based on their core operational focus. Then, simple random sampling was used within each group to ensure that every firm has an equal chance of being selected. This approach enhanced representativeness across all sub-sectors of manufacturing. The distribution of the sample across the sectors was shown in Table 3.2

TABLE 3.2:

Sample Size

Sector	Population	Sample Size
Agro-Processing	857	109
Textiles	691	87
Light Manufacturing	1204	153
TOTAL	**2752**	**349**

3.5 Data Collection Instruments

Data collection refers to the systematic process of gathering and analyzing information related to key research variables, with the aim of addressing research questions, testing hypotheses, and drawing meaningful conclusions (Burns & Burns, 2021). The type of information required in a study often determines the most appropriate data collection instrument. In this study, a structured questionnaire was used to gather primary data from the selected respondents. This primary data was essential in capturing the actual relationship between the independent variables, artificial intelligence tools and the dependent variable, financial decision-making.

The use of a questionnaire was justified due to its efficiency, affordability, and suitability for collecting standardized data from a large sample within a limited timeframe. All questions were closed-ended, which allowed for consistency in responses and facilitates

easier coding and analysis. The questionnaire was organized into three key sections: the first section captured background information of the respondents and firms; the second focused on the adoption and use of artificial intelligence tools (predictive analytics, machine learning, automated reporting, and NLP); and the third assessed aspects of financial decision-making.

3.6 Instrumentation and Data Collection Procedures

Data collection involves the systematic gathering of empirical evidence to provide meaningful insights into a specific phenomenon and to respond to the study's research questions (Khan, 2018). Prior to data collection, the researcher obtained the necessary approvals from relevant regulatory and institutional bodies. The selected respondents were individuals deemed to have sufficient knowledge of both artificial intelligence and financial operations within their respective firms.

To facilitate the process, the researcher administered a structured questionnaire to the head of finance in each of the sampled manufacturing firms, based on the assumption that they were well-informed about the firm's use of AI tools and its financial decision-making processes. The questionnaire was distributed via Google Forms, providing a convenient and efficient digital platform for data submission. Follow-up reminders were sent to non-respondents to enhance the response rate and ensure that the data collected was both comprehensive and representative.

3.7 Pilot Test

Ensuring the accuracy and appropriateness of the research instrument was essential for obtaining reliable results. To this end, a pilot study was conducted to assess the feasibility of the main study and to evaluate the reliability and validity of the questionnaire. The pilot test involved 10% of the total sample size, which translates to 35 respondents, as

recommended by Kothari (2020), who considers 10% of the target population sufficient for a pilot.

The questionnaire was distributed to these 35 respondents (heads of finance) to gather their feedback on the clarity, structure, and relevance of the questions. Participants were encouraged to suggest any necessary improvements to enhance the instrument's consistency and its ability to effectively address the study's objectives. Importantly, the individuals who participated in the pilot test were excluded from the final data collection phase to avoid any potential bias.

3.7.1 Validity of Data Collection Instrument

Validity refers to the extent to which a research instrument accurately captures the concept it is intended to measure (Cooper & Schindler, 2021). In this study, construct validity was ensured by aligning the operational definitions of the variables with their theoretical meanings, thereby confirming that the questionnaire effectively reflects the underlying concepts. To achieve this, the researcher adapted a pre-existing questionnaire from prior empirical studies, making necessary adjustments to ensure alignment with the current research objectives. Additionally, content validity was established through expert review. This involved consultation with academic supervisors who critically assessed the questionnaire to confirm that all relevant aspects of the study variables were adequately covered. Their input helped ensure that the questions were conceptually accurate, logically structured, and consistent with the theoretical framework guiding the study.

3.7.2 Reliability of Data Collection Instrument

Reliability refers to the consistency of a research instrument in producing stable and repeatable results under similar conditions (Cooper & Schindler, 2021). An instrument is considered reliable when it yields consistent outcomes across multiple applications. To

assess the internal consistency of the questionnaire in this study, Cronbach's Alpha was used. This statistical measure evaluated how closely related a set of items were as a group, thereby indicating the reliability of the instrument.

According to Khan (2018), Cronbach's Alpha is particularly useful for determining whether the instrument remains dependable even when slight modifications are made to the items. A Cronbach's Alpha coefficient between 0.7 and 0.8 is generally accepted as satisfactory, while a value above 0.8 is considered highly reliable. The instrument used in this study was evaluated against this threshold to ensure it meets the required standards of reliability. The reliability test results are as shown in Table 3.3

TABLE 3.3:

Reliability Results

Variables	Items	Cronbach Alpha	Remark
Predictive analytics	6	.802	Reliable
Machine learning models	6	.773	Reliable
Automated financial reporting	6	.826	Reliable
Natural language processing tools	6	.737	Reliable
Financial decision-making	6	.905	Reliable

3.8 Data Analysis and Presentation

Data analysis refers to the process of systematically organizing and refining raw data into a structured and scientific format that can be easily interpreted (Burns & Burns, 2021). As noted by Kothari (2020), this process involves a series of interrelated steps aimed at summarizing, coding, and arranging collected data to effectively address the research questions. In this study, the researcher begun by reviewing all completed questionnaires to ensure completeness and accuracy, followed by sorting them based on their suitability for analysis. Each item in the questionnaire was assigned a specific code to facilitate data entry and scoring.

The coded data was entered into SPSS version 28 for analysis. Descriptive statistics such as means (measures of central tendency) and standard deviations (measures of dispersion) were used to analyze patterns in the data and summarize respondents' views. To examine the relationships between the independent variables (AI tools) and the dependent variable (financial decision-making), the study used correlation analysis and multiple regression analysis. The findings were presented using tables, followed by interpretation and discussion aligned with the study objectives.

3.8.1 Model Summary

The regression model below was used:

$$\mathbf{Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon}$$

Where: Y = Financial decision-making

α = regression intercept.

β_1, β_2, β_3, β_4= Model coefficients

X_1 = Predictive analytics

X_2= Machine learning models

X_3= Automated financial reporting

X_4= Natural language processing tools

ε =error term

3.9 Pretesting of Multiple Regression Assumptions

Before conducting multiple regression analysis, it is important to perform diagnostic tests to ensure that the assumptions of the classical linear regression model (CLRM) are not violated. Violations of these assumptions can lead to biased, inefficient, or inconsistent parameter estimates, which compromise the validity of the results. Therefore, this study

undertook a series of diagnostic checks to confirm that the data met the fundamental assumptions of regression analysis.

3.9.1 Normality Test

To assess whether the residuals from the regression model are normally distributed around the mean, normality tests such as the Shapiro-Wilk test and the Kolmogorov-Smirnov test were employed. These statistical tests helped determine if the distribution of the residuals deviates significantly from a normal distribution, which is a key requirement for reliable inference in linear regression.

3.9.2 Multicollinearity Test

The study tested multicollinearity using Variance Inflation Factors (VIF) to examine the strength of relationships among the independent variables. A VIF exceeding 10 was interpreted as an indication of multicollinearity, which can inflate standard errors and destabilize the regression coefficients (Cooper & Schindler, 2021). Identifying and managing multicollinearity is critical to ensuring that the estimated effects of the predictors on the dependent variable are reliable.

3.9.3 Heteroscedasticity

Heteroskedasticity must be identified and addressed to ensure that the assumptions of the Classical Linear Regression Model (CLRM) are upheld. The CLRM assumes that the error term has a constant variance, a condition referred to as homoscedasticity. However, if the variance of the error term is inconsistent across observations, it results in heteroskedasticity. While heteroskedasticity does not bias the coefficient estimates, it distorts the standard errors, potentially leading to unreliable hypothesis testing. In this research, heteroskedasticity was evaluated via the Breusch-Pagan / Cook-Weisberg test, as recommended by Khan (2018). The null hypothesis for this test assumed that the error

variance was homoscedastic. Addressing heteroskedasticity ensured the reliability and validity of the regression results.

3.10 Ethical Considerations

This study adhered to ethical standards to ensure the rights and confidentiality of all participants were protected. Before commencing data collection, all necessary permits and approvals were obtained. Permission to conduct the research was sought from KCA University, and a research authorization permit was secured from the National Commission for Science, Technology, and Innovation (NACOSTI), which regulates and approves research activities in Kenya. Additionally, formal approval was sought from the management of the targeted manufacturing firms to ensure their consent and cooperation in facilitating access to the required staff and resources. Confidentiality was upheld throughout the study, with all collected data securely stored and shared only with the explicit consent of the participants. This ensured their privacy and trust were respected at every stage of the research process.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the study findings on the influence of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County. It covers the response rate, descriptive results, and inferential analysis of the four AI dimensions—predictive analytics, machine learning, automated financial reporting, and natural language processing—in relation to resource allocation, investment planning, cost management, and risk assessment. The results are interpreted and discussed in line with the study objectives, hypotheses, and reviewed literature.

4.2 Response Rate

Table 4.1 presents the response rate obtained from the administered questionnaires. Out of the 349 questionnaires distributed to finance managers in manufacturing firms across Nairobi County, 243 were returned, representing a response rate of 69.6 percent. The remaining 106 questionnaires were unreturned, accounting for 30.4 percent of the total sample. A response rate above 60 percent is generally considered adequate for academic surveys, indicating that the study achieved a sufficient level of participation to provide reliable and valid insights.

The achieved response rate has important implications for the study. First, it ensures that the findings are representative of the targeted population of manufacturing firms, thereby strengthening the generalizability of the results. Second, the high participation rate minimizes the risk of non-response bias, meaning that the conclusions drawn about the effect of artificial intelligence on financial decision-making are likely to reflect the actual

situation in the sector. This robust level of engagement provides a strong foundation for subsequent analysis and enhances the credibility of the study's outcomes.

TABLE 4.1:

Response Rate

Response Rate	Frequency	Percent
Returned	243	69.6
Unreturned	106	30.4
Total	**349**	**100**

4.3 Demographic Characteristics

This section presents the background information of the respondents. It highlights key characteristics including gender, age bracket, and highest education level attained, which provide context for interpreting the findings on artificial intelligence and financial decision-making in manufacturing firms. These demographics are crucial in assessing the diversity of respondents, understanding their capacity to engage with AI tools, and ensuring that the sample adequately represents the study population.

4.3.1 Gender of the Respondents

Table 4.2 presents the gender distribution of the respondents. Out of the 243 finance managers who participated in the study, 132 (54.3 percent) were male while 111 (45.7 percent) were female. This distribution shows that both genders were fairly represented, with males forming a slight majority. The near balance between male and female respondents indicates that perspectives from both groups were well captured, reducing the risk of gender bias in the responses.

The implication of this finding is that the study benefited from diverse insights reflecting the experiences and perceptions of both male and female finance managers in Nairobi's manufacturing firms. Given the increasing emphasis on gender inclusivity in the

workplace, this balance enhances the credibility of the results, as it shows that the analysis on the influence of artificial intelligence on financial decision-making was informed by a gender-diverse pool of professionals. This strengthens the generalizability of the findings to the wider manufacturing sector.

TABLE 4.2:

Gender Distribution

Gender	Frequency	Percentage
Male	132	54.3
Female	111	45.7
Total	**243**	**100**

4.3.2 Age of the Respondents

Table 4.3 shows the age composition of the respondents. The majority, 111 (45.7 percent), were aged between 41 and 50 years, followed by 93 (38.3 percent) in the 31–40 years category. Respondents above 50 years accounted for 30 (12.3 percent), while those below 30 years were the least represented at 9 (3.7 percent). This distribution indicates that most of the finance managers surveyed were in the middle age brackets, suggesting a workforce with considerable professional maturity and stability.

The implication of these findings is that financial decision-making in Nairobi's manufacturing firms is largely driven by individuals in their prime working years, who are likely to combine both professional experience and adaptability to technological changes such as artificial intelligence. The limited representation of respondents below 30 years implies that younger professionals play a smaller role in financial management at the managerial level, while the presence of older respondents above 50 years adds perspectives rooted in long-term industry experience. This balance underscores the reliability of the

findings, as it reflects input from respondents with the expertise and exposure necessary to assess the role of AI in financial decision-making.

TABLE 4.3:

Respondents' Age Composition

Age	Frequency	Percentage
Below 30 years	9	3.7
31-40 years	93	38.3
41-50 years	111	45.7
Above 50 years	30	12.3
Total	**243**	**100**

4.3.3 Highest Level of Education

Table 4.4 presents the highest level of education attained by the respondents. The majority, 126 (51.9 percent), held a bachelor's degree, while 72 (29.6 percent) had attained a master's degree. Respondents with diploma qualifications accounted for 42 (17.3 percent), and only 3 (1.2 percent) possessed PhD qualifications. This distribution shows that most finance managers in Nairobi's manufacturing firms are well educated, with over four-fifths holding degree-level qualifications or higher.

The implication of this finding is that the respondents had the academic background necessary to understand and engage with advanced tools such as artificial intelligence in financial decision-making. The strong representation of degree and master's holders reflects a skilled workforce that is capable of interpreting financial data and adopting new technologies. Although PhD holders were few, their presence indicates some level of advanced specialization within the sector. The relatively high educational attainment across the sample enhances the credibility of the study findings, as it suggests that the respondents were competent to provide informed perspectives on the influence of AI on financial decision-making

TABLE 4.4:

Highest Level of Education

Education	Frequency	Percentage
Diploma	42	17.3
Degree	126	51.9
Masters	72	29.6
PhD	3	1.2
Total	**243**	**100%**

4.3.4 Years of Experience with the Firm

Table 4.5 shows the respondents' years of experience with their respective firms. The majority, 135 (55.6 percent), had worked in their organizations for between 4 and 5 years, while 57 (23.4 percent) had served for more than 5 years. Respondents with 2–3 years of experience accounted for 42 (17.3 percent), and only 9 (3.7 percent) had been with their firms for less than one year. This distribution suggests that most of the finance managers had accumulated substantial tenure within their organizations, reflecting familiarity with firm operations and decision-making processes.

The implication of these results is that the study drew responses from individuals with adequate institutional knowledge and professional experience to provide reliable insights into the influence of artificial intelligence on financial decision-making. The dominance of respondents with more than four years of service indicates that the findings reflect the views of finance managers who have both stability and a deep understanding of firm-level financial practices. The relatively smaller proportion of newer employees ensures that fresh perspectives are also represented, while the strong presence of experienced managers enhances the credibility and applicability of the study's outcomes.

TABLE 4.5:

Years of Experience with the Firm

Number of years	Frequency	Percentage
0-1 years	9	3.7
2-3 years	42	17.3
4-5 years	135	55.6
Above 5 years	57	23.4
Total	**243**	**100%**

4.4 Descriptive Statistics

This section presents the descriptive statistics of the study variables, which provide an overview of how respondents rated the influence of artificial intelligence dimensions—predictive analytics, machine learning models, automated financial reporting, and natural language processing—on financial decision-making. The results are summarized using means and standard deviations to show the central tendencies and variations in responses, offering initial insights into patterns that inform the subsequent inferential analysis.

4.4.1 Predictive Analytics

Table 4.6 presents the descriptive statistics on the influence of predictive analytics on financial decision-making in manufacturing firms. The overall mean score of 3.54 with a standard deviation of 0.60 suggests that respondents generally agreed that predictive analytics plays a moderate to high role in guiding financial practices. Among the individual items, the highest mean scores were recorded for the statements that predictive analytics enhances budgeting accuracy (M = 4.20, SD = 0.40) and that the finance team regularly uses forecasting software (M = 4.10, SD = 0.30). These results indicate that predictive analytics is most strongly associated with improving budgeting precision and supporting consistent use of technological tools in financial planning.

The findings also show that reliance on data trends to guide financial planning was fairly strong (M = 3.71, SD = 0.78), while predictive models assisting in setting financial targets received moderate agreement (M = 3.42, SD = 0.91). These results suggest that, beyond budgeting, predictive analytics contributes to broader financial planning and target-setting, though with slightly lower consistency among respondents. The moderate variation in standard deviations for these items indicates differences in how widely such practices are applied across firms, likely reflecting disparities in technological readiness and resource allocation.

Conversely, predictive analytics was rated lower in terms of helping firms anticipate future financial risks (M = 2.72, SD = 1.00). This implies that while predictive tools are well integrated into routine budgeting and forecasting, their use for risk assessment remains limited. Similarly, the statement on predictive analytics improving overall financial forecasting scored modestly (M = 3.11, SD = 1.14), showing variability across firms in adopting advanced forecasting practices. The relatively higher standard deviations here highlight significant differences in how firms perceive and utilize predictive tools for forward-looking decision-making.

The implication of these findings is that manufacturing firms in Nairobi County are beginning to embrace predictive analytics, particularly in areas that directly improve budgeting efficiency and routine financial processes. However, the comparatively low application of predictive tools in risk anticipation suggests a missed opportunity for firms to proactively manage uncertainties in their financial environments. These results point to the need for increased investment in predictive risk management systems and training for finance teams to maximize the strategic value of predictive analytics in financial decision-making.

TABLE 4.6:

Descriptive Statistics for Predictive Analytics

Statements	N	Mean	Std. Dev
Our firm uses predictive analytics to improve financial forecasting.	243	3.11	1.14
Predictive tools help us anticipate future financial risks.	243	2.72	1.00
Predictive analytics enhances our budgeting accuracy.	243	4.20	0.40
We rely on data trends to guide financial planning.	243	3.71	0.78
Predictive models assist in setting financial targets.	243	3.42	0.91
The finance team regularly uses forecasting software.	243	4.10	0.30
Overall mean Score	**243**	**3.54**	**0.60**

4.4.2 Machine Learning Models

Table 4.7 presents the descriptive statistics on the influence of machine learning (ML) models on financial decision-making. The overall mean score of 3.86 with a standard deviation of 0.43 indicates that respondents generally agreed that ML tools significantly contribute to financial decision-making in manufacturing firms. The highest mean scores were observed for the use of machine learning to support investment decisions (M = 4.10, SD = 0.30) and to detect financial anomalies early (M = 4.10, SD = 0.30). These findings suggest that ML is particularly valued for enhancing investment analysis and strengthening internal controls through early anomaly detection.

The results further show that financial strategies driven by algorithmic insights (M = 4.01, SD = 0.44) and the improved accuracy of financial analysis (M = 4.01, SD = 0.44) were also highly rated. This indicates that ML is increasingly embedded into strategic financial processes, enabling more precise analysis and supporting evidence-based decisions. The relatively low standard deviations in these items suggest consensus among

respondents, reflecting a strong acknowledgment of ML's contribution to analytical rigor and strategic financial management in the sector.

On the other hand, adoption of ML for real-time financial decision-making recorded a moderate mean score of 3.02 with a higher standard deviation (SD = 1.09), pointing to uneven uptake across firms. This variability highlights the challenges of integrating ML into fast-paced, day-to-day decision environments, likely due to infrastructural constraints or limited technical expertise. Additionally, the statement that teams are trained to interpret ML results scored relatively high (M = 3.91, SD = 0.70), but with more variation than other items, suggesting that while training is taking place, its consistency and depth differ across organizations.

The implication of these findings is that manufacturing firms in Nairobi County are effectively using ML models in areas that enhance long-term investment planning, anomaly detection, and overall accuracy of financial analysis. However, the limited application of ML in real-time decision-making reflects a gap in technological integration and responsiveness. Bridging this gap would require firms to strengthen digital infrastructure and invest in continuous training to empower finance teams to apply ML insights in dynamic environments. Overall, the results underscore that ML is a growing strategic resource that, if fully leveraged, can significantly improve financial decision-making in the manufacturing sector.

TABLE 4.7:

Descriptive Statistics for Machine Learning Models

Statements	N	Mean	Std. Dev
We use machine learning to support investment decisions.	243	4.10	0.30
ML models help detect financial anomalies early.	243	4.10	0.30
Our financial strategies are driven by algorithmic insights.	243	4.01	0.44
Machine learning improves the accuracy of financial analysis.	243	4.01	0.44
We have adopted ML for real-time financial decision-making.	243	3.02	1.09
Our team is trained to interpret machine learning results.	243	3.91	0.70
Overall Mean Score	**243**	**3.86**	**0.43**

4.4.3 Automated Financial Reporting

Table 4.8 presents the descriptive statistics on automated financial reporting. The overall mean score of 4.02 with a standard deviation of 0.24 indicates strong agreement among respondents that automation significantly supports financial reporting functions in manufacturing firms. The highest-rated items were that automated reporting has improved financial transparency (M = 4.10, SD = 0.30) and that financial reports are accessible in real-time through systems (M = 4.10, SD = 0.30). These findings demonstrate that automation is strongly associated with enhancing openness, accountability, and timely access to financial information, which are critical in supporting effective decision-making.

The results also show that automation reduces reporting errors (M = 4.00, SD = 0.00) and that financial reports are generated using automation tools (M = 4.00, SD = 0.00). The absence of variation in these responses highlights a unanimous agreement among respondents, suggesting that automation has been widely adopted and standardized across the sector to ensure accuracy and consistency in reporting. This widespread acceptance underscores the importance of automated tools in minimizing human error and improving data reliability.

Additionally, respondents agreed that automated systems have improved reporting timeliness (M = 4.00, SD = 0.45) and that software is used to compile monthly financial statements (M = 3.90, SD = 0.54). While these results are also strong, the slightly higher standard deviations reflect some differences in the speed of adoption and the extent to which different firms rely on automation for routine reporting functions. This variation suggests that while automation is broadly embraced, the degree of implementation may vary depending on firm size, resources, or level of technological investment.

The implication of these findings is that manufacturing firms in Nairobi County have integrated automated financial reporting into their operations with notable success. By reducing errors, improving transparency, and enabling real-time access, automation has enhanced the reliability and timeliness of financial information, thereby supporting informed decision-making. However, the small variations observed in the use of software for monthly reporting point to differences in system capacity across firms, highlighting the need for continued investment in digital infrastructure to ensure uniform benefits across the sector.

TABLE 4.8:

Descriptive Statistics for Automated Financial Reporting

Statements	N	Mean	Std. Dev
Our financial reports are generated using automation tools.	243	4.00	0.00
Automation reduces reporting errors in our firm.	243	4.00	0.00
Automated systems have improved reporting timeliness.	243	4.00	0.45
We use software to compile monthly financial statements.	243	3.90	0.54
Automated reporting has improved financial transparency.	243	4.10	0.30
Financial reports are accessible in real-time through our systems.	243	4.10	0.30
Overall Mean Score	**243**	**4.02**	**0.24**

4.4.4 Natural Language Processing Tools

Table 4.9 presents the descriptive statistics on the use of natural language processing (NLP) tools in financial decision-making. The overall mean score of 3.92 with a low standard deviation of 0.15 indicates that respondents strongly agreed that NLP contributes significantly to enhancing financial processes in their firms. The highest mean score was observed in the statement that NLP tools enhance interpretation of policy documents (M = 4.10, SD = 0.30), highlighting the important role NLP plays in simplifying regulatory and policy-related texts, which are often complex but critical in guiding financial strategies.

The results also show very strong agreement in three areas where all respondents gave identical ratings: sentiment analysis supports financial decision-making (M = 4.00, SD = 0.00), NLP helps summarize financial reports (M = 4.00, SD = 0.00), and NLP improves understanding of complex financial texts (M = 4.00, SD = 0.00). These unanimous responses emphasize the effectiveness of NLP in streamlining large volumes of financial information into manageable and actionable insights, thereby supporting quick and accurate decision-making across the manufacturing sector.

Respondents also agreed that their firms use NLP to extract key financial insights (M = 3.90, SD = 0.30), showing consistency in the adoption of NLP for knowledge extraction and interpretation. However, the statement that NLP tools help analyze financial documents faster recorded a slightly lower mean score (M = 3.51, SD = 0.67), suggesting variability in perceptions of efficiency gains. This variation could be due to differences in system sophistication, training levels, or the extent to which NLP applications have been integrated into daily financial workflows.

The implication of these findings is that NLP has emerged as a valuable tool for financial decision-making in manufacturing firms, particularly in enhancing

comprehension, summarization, and interpretation of financial and policy documents. While adoption is strong across most areas, the relatively lower rating for document analysis speed indicates that some firms may not be fully exploiting NLP's potential for efficiency. Addressing these gaps through improved system integration and capacity-building initiatives could further enhance the contribution of NLP tools to financial decision-making in Nairobi's manufacturing sector.

TABLE 4.9:

Descriptive Statistics for Natural Language Processing Tools

Statements	N	Mean	Std. Dev
NLP tools help us analyze financial documents faster.	243	3.51	0.67
Our firm uses NLP to extract key financial insights.	243	3.90	0.30
Sentiment analysis supports financial decision-making.	243	4.00	0.00
We rely on NLP to summarize financial reports.	243	4.00	0.00
NLP improves understanding of complex financial texts.	243	4.00	0.00
NLP tools enhance our interpretation of policy documents.	243	4.10	0.30
Overall Mean Score	**243**	**3.92**	**0.15**

4.4.5 Financial Decision-Making

Table 4.10 presents the descriptive statistics on financial decision-making practices in manufacturing firms. The overall mean score of 3.94 with a standard deviation of 0.43 indicates that respondents generally agreed that their firms adopt effective and structured financial decision-making processes. The highest-rated items were the effectiveness of cost management strategies (M = 4.10, SD = 0.30) and alignment of financial decisions with long-term goals (M = 4.10, SD = 0.30). These findings suggest that cost control and strategic alignment are key priorities for finance managers, reflecting a focus on sustainability and profitability in decision-making.

The results also show that risk assessments play a significant role in guiding financial decisions (M = 4.01, SD = 0.63), emphasizing the importance of proactive risk management in a dynamic business environment. The relatively higher standard deviation here indicates variability in how firms approach risk assessment, possibly reflecting differences in firm size, resources, and exposure to financial uncertainties. Nonetheless, the positive mean score highlights a growing recognition of risk evaluation as a critical component of sound financial management.

Moderate agreement was recorded for the statement that investment planning is based on accurate forecasts (M = 3.61, SD = 0.67). This suggests that while forecasting plays a role in shaping investment decisions, there may be challenges in ensuring accuracy and consistency across firms. Variability in responses points to disparities in forecasting capabilities, likely influenced by differences in technological adoption and data quality. Meanwhile, financial decisions being data-driven and timely (M = 3.90, SD = 0.54) and efficient resource allocation (M = 3.90, SD = 0.54) were also rated positively, showing that firms are gradually moving toward evidence-based decision-making.

The implication of these findings is that manufacturing firms in Nairobi County are fairly effective in their financial decision-making, with notable strengths in cost management, long-term strategic alignment, and incorporation of risk assessments. However, areas such as investment planning accuracy and timeliness of decisions reveal opportunities for improvement, particularly through enhanced forecasting techniques and adoption of advanced tools like AI. These results underscore the need for firms to strengthen their data-driven approaches to ensure that financial decisions consistently support growth, efficiency, and resilience in a competitive business environment.

TABLE 4.10:

Descriptive Statistics for Financial Decision-Making

Statement	N	Mean	Std. Dev.
Our financial decisions are data-driven and timely.	243	3.90	0.54
We allocate financial resources efficiently.	243	3.90	0.54
Investment planning is based on accurate forecasts.	243	3.61	0.67
We have effective strategies for cost management.	243	4.10	0.30
Risk assessments guide our financial decisions.	243	4.01	0.63
Financial decisions support our firm's long-term goals.	243	4.10	0.30
Average	**243**	**3.94**	**0.43**

4.5 Correlation Analysis

Correlation analysis was conducted to determine the nature and strength of the relationships between artificial intelligence dimensions and financial decision-making in manufacturing firms. Pearson's correlation coefficient was used, which measures the degree of linear association between variables, with values ranging from -1 to +1. A positive correlation implies that as one variable increases, the other also increases, while a negative correlation suggests an inverse relationship. Significance was tested at the 5 percent level, meaning that associations with p-values below 0.05 were considered statistically significant.

The results indicate that predictive analytics had a strong and significant positive correlation with financial decision-making ($r = 0.830$, $p < 0.01$). This implies that greater adoption of predictive analytics tools is associated with improved financial outcomes such as more accurate forecasting, efficient budgeting, and effective resource allocation. The strength of this relationship highlights predictive analytics as a key driver of financial decision-making in manufacturing firms within Nairobi County.

Similarly, machine learning models also showed a strong and positive correlation with financial decision-making ($r = 0.833$, $p < 0.01$). This result suggests that the integration of machine learning enhances financial decisions by improving anomaly detection, investment planning, and financial analysis accuracy. The correlation is slightly stronger than that of predictive analytics, underscoring the potential of machine learning as a strategic resource for data-driven decision-making when appropriately embedded in financial operations.

Automated financial reporting was also significantly correlated with financial decision-making ($r = 0.709$, $p < 0.01$). Although weaker than predictive analytics and machine learning, the correlation is still strong, suggesting that automation improves timeliness, transparency, and accuracy of financial information, which in turn supports better decision outcomes. The result highlights the contribution of automation in streamlining reporting processes and enhancing reliability of financial data.

Natural language processing tools showed a moderate but significant positive correlation with financial decision-making ($r = 0.552$, $p < 0.01$). While this correlation is weaker than the other AI dimensions, it still indicates that NLP contributes positively, particularly by enhancing comprehension of complex financial texts, summarizing reports, and interpreting policy documents. This moderate relationship suggests that NLP is still an emerging tool in the sector, with potential for greater impact as adoption deepens.

TABLE 4.11:

Correlation Results

		Financial decision-making	Predictive analytics	Machine learning models	Automated financial reporting	Natural language processing tools
Financial decision-making	Pearson Correlation	1				
	Sig. (2-tailed)					
Predictive analytics	Pearson Correlation	.830**	1			
	Sig. (2-tailed)	.000				
Machine learning models	Pearson Correlation	.833**	.669**	1		
	Sig. (2-tailed)	.000	.000			
Automated financial reporting	Pearson Correlation	.709**	.634**	.696**	1	
	Sig. (2-tailed)	.000	.000	.000		
Natural language processing tools	Pearson Correlation	.552**	.552**	.454**	.417**	1
	Sig. (2-tailed)	.000	.000	.000	.000	

**. Correlation is significant at the 0.01 level (2-tailed).
b. Listwise N=243

4.6 Diagnostic Tests

This section presents the diagnostic tests conducted to ensure the validity and reliability of the regression model used in the study. These tests include assessments for normality, multicollinearity, and heteroscedasticity to verify that the data meet the assumptions of the classical linear regression model, thereby ensuring accurate and unbiased results.

4.6.1 Tests of Normality

Table 4.12 presents the results of the Shapiro-Wilk test for normality for the study variables, including predictive analytics, machine learning models, automated financial reporting, natural language processing tools, and financial decision-making. The Shapiro-Wilk test is used to determine whether the data are normally distributed. For each variable, the test

provides a statistic and a significance value (Sig.). A significant value greater than 0.05 indicates that the data do not significantly deviate from a normal distribution.

The results show that all the study variables have significance values (Sig.) well above the 0.05 threshold: predictive analytics (.723), machine learning models (.784), automated financial reporting (.815), natural language processing tools (.820), and financial decision-making (.812). These high significance values suggest that the null hypothesis of normality cannot be rejected, indicating that the data for all the variables are normally distributed. This supports the validity of subsequent parametric tests and regression analysis, as the assumption of normality is satisfied for the dataset.

TABLE 4.12:

Test of Normality

	Shapiro-Wilk		
Study variables	Statistic	Df	Sig.
Predictive analytics	.881	243	.723
Machine learning models	.892	243	.784
Automated financial reporting	.901	243	.815
Natural language processing tools	.907	243	.820
Financial decision-making	.874	243	.812

4.6.2 Tests of Multicollinearity

Table 4.13 presents the results of the multicollinearity test for the independent variables, using Variance Inflation Factor (VIF) and Tolerance values. Multicollinearity occurs when independent variables in a regression model are highly correlated, which can inflate the standard errors and make it difficult to determine the individual effect of each variable. A VIF value greater than 10 indicates significant multicollinearity, while a Tolerance value below 0.1 suggests high multicollinearity.

The VIF values for all variables are below the threshold of 10, with Predictive Analytics having a VIF of 4.071, machine learning models 3.507, automated financial reporting 3.807, and natural language processing tools 3.655. The Tolerance values are all above 0.1, with predictive analytics at .246, machine learning models at .285, automated financial reporting at .263, and natural language processing tools at .274. These results indicate that multicollinearity is not a significant concern in this study, as the VIF values are well within acceptable limits and Tolerance values are sufficiently high. The mean VIF value of 3.648 further supports that multicollinearity is not problematic, ensuring that the regression model's estimates will be reliable and accurate.

TABLE 4.13:

Test of Multicollinearity

Variable	VIF	Tolerance
Predictive Analytics	4.071	.246
Machine Learning Models	3.507	.285
Automated Financial Reporting	3.807	.263
Natural Language Processing Tools	3.655	.274
Mean VIF	3.648	

4.6.3 Tests of Heteroscedasticity

Table 4.14 presents the results of the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity. Heteroscedasticity occurs when the variance of the error terms in a regression model is not constant, which can lead to inefficient estimates and invalid statistical inferences. The test provides a chi-square (chi2) statistic and an associated p-value (Prob > chi2). A p-value greater than 0.05 indicates that heteroscedasticity is not a concern.

The chi-square statistic is 0.8326, and the p-value is 0.6214, which is well above the 0.05 threshold. This indicates that the null hypothesis of homoscedasticity (constant

variance of the error terms) cannot be rejected. Therefore, the results suggest that there is no evidence of heteroscedasticity in the regression model, ensuring that the estimates obtained from the regression analysis will be efficient and the statistical inferences valid.

TABLE 4.14:

Test of Heteroscedasticity

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity		
chi2(1)	=	0.8326
Prob > chi2	=	0.6214

4.7 Regression Analysis

This section presents the regression analysis conducted to establish the combined and individual effects of artificial intelligence dimensions—predictive analytics, machine learning models, automated financial reporting, and natural language processing tools—on financial decision-making in manufacturing firms. The model fitness, analysis of variance (ANOVA), and regression coefficients are reported and interpreted to show the explanatory power of the model, its overall significance, and the contribution of each predictor variable to financial decision-making.

The regression model achieved a strong correlation coefficient (R = 0.882), indicating a high level of association between the independent variables and financial decision-making. The coefficient of determination ($R^2 = 0.777$) shows that 77.7 percent of the variation in financial decision-making is explained by the four AI dimensions, while the adjusted R^2 (0.773) confirms that the model remains robust after accounting for the number of predictors. The standard error of the estimate (0.207) is relatively low, suggesting that the predicted values closely approximate the observed values. These results

imply that AI dimensions are powerful predictors of financial decision-making among manufacturing firms in Nairobi County.

TABLE 4.15:

Model Fitness

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.882[a]	.777	.773	.206715905568673

a. Predictors: (Constant), Natural language processing tools, Automated financial reporting, Predictive analytics, Machine learning models

The ANOVA results indicate that the model was statistically significant ($F = 207.497$, $p < 0.001$). This demonstrates that the four AI dimensions, when taken together, significantly influence financial decision-making. The large F-statistic further supports the strength of the overall model, confirming that the predictors jointly provide meaningful explanatory power beyond what could be expected by chance. Thus, the regression model is appropriate for assessing the impact of AI on financial decision-making outcomes.

TABLE 4.16:

Analysis of Variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35.467	4	8.867	207.497	.000[b]
	Residual	10.170	238	.043		
	Total	45.637	242			

a. Dependent Variable: Financial decision-making

b. Predictors: (Constant), Natural language processing tools, Automated financial reporting, Predictive analytics, Machine learning models

The regression coefficients show that all four AI dimensions significantly contribute to financial decision-making at the 5 percent significance level. Machine learning models had the highest standardized beta coefficient ($\beta = 0.349$, $p < 0.001$),

indicating it is the most influential predictor, followed closely by predictive analytics (β = 0.325, p < 0.001). Automated financial reporting also had a strong positive effect (β = 0.206, p < 0.001), while natural language processing tools, though comparatively weaker, still had a significant positive effect (β = 0.128, p = 0.001). These results suggest that while all dimensions are important, machine learning and predictive analytics provide the strongest contributions to effective financial decision-making.

TABLE 4.17:

Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-1.125	.410		-2.742	.007
	Predictive analytics	.234	.048	.325	4.903	.000
	Machine learning models	.350	.068	.349	5.176	.000
	Automated financial reporting	.366	.077	.206	4.778	.000
	Natural language processing tools	.360	.105	.128	3.441	.001

a. Dependent Variable: Financial Decision-Making

The following is the regression model that was estimated from the study results:

$$\mathbf{Y = -1.125 + 0.234X_1 + 0.350X_2 + 0.366X_3 + 0.360X_4}$$

Where:

Y = Financial Decision-Making,

X_1 – Predictive Analytics,

X_2 – Machine Learning Models,

X_3 – Automated Financial Reporting,

X_4 – Natural Language Processing Tools

4.8 Hypotheses Testing

This section presents the testing of the study's hypotheses to determine whether the proposed relationships between artificial intelligence dimensions and financial decision-making in manufacturing firms are statistically supported. Using regression coefficients and significance values at the 5 percent level, each null hypothesis is evaluated against the empirical results, providing evidence on whether to accept or reject the hypotheses in line with the study objectives.

4.8.1 Predictive Analytics and Financial Decision-Making

The first hypothesis stated that predictive analytics has no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya. The regression results revealed that predictive analytics had a positive and statistically significant effect on financial decision-making ($\beta = 0.325$, $p < 0.001$). Since the significance value was below the 5 percent threshold, the null hypothesis was rejected. This finding implies that predictive analytics meaningfully contributes to improved budgeting accuracy, forecasting, and resource allocation among manufacturing firms in Nairobi County.

From a theoretical perspective, these findings align with the Technology Acceptance Model (TAM), which posits that perceived usefulness and ease of use drive technology adoption. Finance managers who view predictive analytics as valuable for enhancing forecasting and budgeting are more likely to integrate it into decision-making processes. The study confirms this, as predictive analytics demonstrated a strong influence on financial outcomes, reflecting both behavioral intention and actual adoption predicted by TAM. This strengthens the argument that user perceptions play a critical role in determining the success of predictive tools in financial decision-making contexts.

The results also resonate with global empirical studies. For instance, Hossain et al. (2024) and Zong and Guan (2024) showed that predictive analytics improved investment planning and credit risk management in Pakistani and Chinese manufacturing firms, respectively. Similarly, Lee et al. (2022) found predictive tools valuable for budgeting and cash flow forecasting in Malaysian firms. The current study corroborates these findings by confirming that predictive analytics enhances forecasting and planning in Nairobi-based firms. However, unlike the global studies that often focus on large, resource-rich firms, this study demonstrates that predictive analytics is also relevant in emerging market contexts, albeit with varying levels of adoption.

Regionally, the findings extend the limited evidence available. Maganga and Taifa (2023) observed that predictive analytics supported risk management among East African conglomerates, while Mogaka (2023) linked it to procurement efficiency in Kenya's food processing sector. However, these studies did not explicitly connect predictive analytics to core financial decision-making processes. By showing that predictive analytics significantly influences budgeting, investment planning, cost management, and risk assessment, this study addresses the contextual gap and offers localized evidence for its strategic value.

Furthermore, the results highlight methodological advancements over prior research. While earlier studies often relied on secondary data or descriptive designs (e.g., Maganga & Taifa, 2023; Odesanya & Odigie, 2022), the current study applied regression analysis to establish causal relationships. This not only strengthens the empirical basis for predictive analytics' role but also demonstrates how its application can extend beyond operational efficiency to strategic financial outcomes. In doing so, the study bridges both the conceptual and methodological gaps in existing literature and provides practical

evidence that predictive analytics is a key enabler of financial decision-making in Nairobi's manufacturing firms.

4.8.2 Machine Learning Models and Financial Decision-Making

The second hypothesis stated that machine learning models have no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya. The regression results revealed that machine learning models had a positive and statistically significant effect on financial decision-making ($\beta = 0.349$, $p < 0.001$). Since the p-value was below the 5 percent level, the null hypothesis was rejected. This indicates that the use of machine learning significantly enhances financial decisions, particularly by supporting investment planning, anomaly detection, and accurate financial analysis in manufacturing firms.

From a theoretical standpoint, these findings align with the Resource-Based View (RBV), which emphasizes that firms gain competitive advantage from unique resources and capabilities. Machine learning models represent a form of intangible resource that, when effectively embedded in firm processes, can strengthen decision-making capabilities and create sustained value. By improving forecasting, optimizing budgeting, and detecting financial irregularities, ML tools enhance not just performance outcomes but also the quality and reliability of the decision-making process itself. The results thus support the RBV argument that technological capabilities can act as strategic assets in dynamic financial environments.

The findings also resonate with studies from developed economies. Nguyen (2024) observed that ML improved capital allocation and investment returns in Vietnamese corporate finance systems, while Wasserbacher and Spindler (2022) noted the sophistication of ML in automating financial models and detecting anomalies. The current

study corroborates these insights by showing that ML tools significantly influence financial decisions in Nairobi's manufacturing sector. However, unlike the global studies that largely rely on secondary data or theoretical models, the present study demonstrates the practical, manager-level adoption of ML in decision-making, thereby addressing the conceptual gap around behavioral and cognitive dimensions.

In emerging economies, earlier work by Hossain et al. (2025) showed that ML reduced expenditure variances in Bangladeshi firms, and Ashtiani and Raahemi (2021) demonstrated its usefulness in fraud detection in Indian manufacturing contexts. However, these studies did not fully explore strategic decisions such as capital budgeting or investment planning. The current findings advance this body of work by providing evidence that ML contributes directly to financial decision-making outcomes such as resource allocation, cost control, and risk assessment in Nairobi's firms. This extends the discussion beyond operational applications to core strategic financial choices.

Regionally and locally, the study builds on and extends the limited research available. Masila (2023) linked ML and big data capabilities to profitability and cost control in Kenyan manufacturers but focused mainly on performance outcomes. Macharia (2023) highlighted ML in Nairobi's startups, while Mwangi (2024) emphasized supply chain applications. These studies underscore the contextual and sectoral gaps in understanding ML's role in financial decision-making. By showing that ML has a significant effect on budgeting, investment planning, cost management, and risk assessment, the current study addresses both the contextual and theoretical gaps, offering Kenya-specific evidence that strengthens the case for ML as a strategic decision-making resource.

4.8.3 Automated Financial Reporting and Financial Decision-Making

The third hypothesis stated that automated financial reporting has no significant effect on financial decision-making in manufacturing firms in Nairobi County, Kenya. The regression results revealed that automated financial reporting had a positive and statistically significant effect on financial decision-making ($\beta = 0.206$, $p < 0.001$). Since the significance value was below the 5 percent threshold, the null hypothesis was rejected. This implies that automated reporting systems significantly enhance financial decision-making by improving transparency, accuracy, and timeliness, thereby supporting budgeting, cost management, and risk assessment functions within manufacturing firms.

The findings can be understood through the lens of Automation Theory, which posits that automated systems reduce human error, increase efficiency, and improve consistency in information processing. In the context of this study, automated reporting tools not only minimize reporting errors but also make financial information more accessible and reliable, enabling managers to make quicker and more informed decisions. This supports the argument that automation enhances not just compliance but also the strategic use of financial information in decision-making.

The results resonate with global evidence. Alao et al. (2024) showed that automation reduced reporting errors and improved compliance in U.S. corporations, while Wang et al. (2024) found automation beneficial in manufacturing, albeit focusing on product-related rather than financial decisions. The current study extends these insights by empirically confirming that automation contributes directly to financial decision-making outcomes in manufacturing firms, addressing the conceptual gap in prior studies that emphasized efficiency over decision quality.

In the Kenyan context, earlier studies have documented automation's benefits in government and financial sectors. Barngetuny (2024) linked automation to workflow efficiency in the Ministry of Finance, while Ibrahim (2022) noted its role in compliance under IFRS 9 within banks. However, these studies did not directly assess internal financial decision-making. More relevantly, Mohammed (2022) found that automated reporting improved budgeting accuracy in Kenyan manufacturing firms, and Wekesa (2022) reported compliance gains in pharmaceutical firms. The current study broadens these findings by demonstrating that automation influences multiple financial decision dimensions—budgeting, investment planning, cost management, and risk assessment—thereby filling the empirical gap.

Furthermore, the findings align with insights from ERP and enterprise systems research. Jayeola et al. (2022) showed ERP systems improved planning and reporting, while Lekorere (2022) linked automation to compliance and decision speed in banks. Although valuable, such studies emphasized leadership or organizational outcomes, often overlooking the decision-making behavior of finance professionals. By integrating primary data from finance managers, this study provides behavioral insights consistent with Cognitive Fit Theory, which suggests that the structure and presentation of financial data influence decision accuracy. In doing so, the study extends the theoretical conversation and highlights that automated financial reporting not only enhances efficiency but also strengthens the quality of financial decision-making in resource-constrained manufacturing contexts.

4.8.4 Natural Language Processing Tools and Financial Decision-Making

The fourth hypothesis stated that natural language processing (NLP) tools have no significant effect on financial decision-making in manufacturing firms in Nairobi County,

Kenya. The regression results revealed that NLP tools had a positive and statistically significant effect on financial decision-making ($\beta = 0.128$, $p = 0.001$). Since the p-value was below the 5 percent threshold, the null hypothesis was rejected. This means that NLP tools play a meaningful role in enhancing budgeting, cost management, and risk assessment, though their effect is comparatively weaker than that of predictive analytics, machine learning, or automated reporting.

From a theoretical perspective, these findings align with the Cognitive Fit Theory, which argues that decision accuracy improves when the format of information aligns with the nature of the decision task. By enabling finance professionals to quickly interpret complex financial texts, summarize reports, and analyze unstructured data, NLP reduces cognitive load and enhances decision efficiency. The significant but modest influence of NLP reflects its emerging role in financial decision-making: while not yet as dominant as other AI tools, it is nonetheless contributing to improving the interpretability of financial information in manufacturing firms.

The findings also build on global literature that has often linked NLP to reporting and compliance. Oyewole et al. (2024) documented improvements in accuracy and speed through NLP in automating reporting, while Anton et al. (2024) found that chatbots enhanced communication and accessibility in Romanian accounting firms. However, both studies focused more on external reporting functions than on internal decision-making. The current study advances this discussion by empirically demonstrating that NLP tools support financial decision-making at the managerial level, addressing the conceptual gap around how NLP shapes financial judgment and strategic planning.

In emerging and sector-specific contexts, Hu et al. (2025) highlighted NLP's role in improving data extraction in African public health, while Chimeudeonwo (2023)

reported its utility in electric vehicle manufacturing operations. Yet, neither examined its application in financial decision contexts. Similarly, Kenyan studies like Ndegwa (2024) and Guo and Polak (2024) touched on readability and enterprise intelligence but did not isolate NLP's role in financial decision-making. By showing that NLP significantly influences budgeting, cost management, and risk assessment, this study extends the regional literature and demonstrates NLP's strategic relevance in Nairobi's manufacturing sector.

Finally, the study contributes methodologically by filling an empirical gap left by earlier conceptual and descriptive research. Unlike system-based reviews (e.g., Hu et al., 2025; Oyewole et al., 2024), which relied heavily on secondary data or theoretical models, this study used primary data from finance managers to capture behavioral and cognitive dimensions of NLP adoption. This provides a clearer picture of how professionals interact with NLP tools and how these tools shape financial decision outcomes in practice. Thus, the study not only confirms the value of NLP in decision-making but also highlights its growing importance as manufacturing firms in emerging economies move toward more data-driven, AI-supported financial environments.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter provides a synthesis of the study by presenting a summary of the key findings, drawing conclusions based on the research objectives, and outlining recommendations for policy, practice, and further research. The summary highlights the major results from the analysis of how artificial intelligence dimensions influence financial decision-making in manufacturing firms in Nairobi County. The conclusions distill these findings into broader insights that address the study objectives, while the recommendations propose practical actions for managers, policymakers, and future scholars.

5.2 Summary

This section summarizes the key findings of the study in line with the specific objectives, highlighting how each dimension of artificial intelligence—predictive analytics, machine learning models, automated financial reporting, and natural language processing tools—affects financial decision-making in manufacturing firms in Nairobi County. The summary distills the results of descriptive, correlation, and regression analyses into concise insights that demonstrate the extent to which AI tools contribute to budgeting, investment planning, cost management, and risk assessment.

5.2.1 Predictive Analytics and Financial Decision-Making

The first objective of the study was to establish the effect of predictive analytics on financial decision-making in manufacturing firms in Nairobi County. Descriptive results showed that predictive analytics was widely applied to enhance budgeting accuracy ($M = 4.20$, $SD = 0.40$) and in the use of forecasting software ($M = 4.10$, $SD = 0.30$). However, its role in anticipating future financial risks was rated moderately ($M = 2.72$, $SD = 1.00$), suggesting

uneven adoption across firms. Correlation analysis revealed a strong positive and significant relationship between predictive analytics and financial decision-making ($r = 0.830$, $p < 0.01$), while regression analysis confirmed that predictive analytics had a statistically significant effect ($\beta = 0.325$, $p < 0.001$), leading to the rejection of the null hypothesis.

These findings indicate that predictive analytics contributes significantly to improving the quality of financial decision-making, particularly in budgeting, forecasting, and setting financial targets. The results also highlight that while predictive analytics is moderately applied for risk anticipation, it remains a critical tool for enhancing data-driven decision-making processes. Overall, the evidence demonstrates that predictive analytics is a key driver of financial decisions within Nairobi's manufacturing sector, reinforcing its importance as an enabler of effective planning, efficient resource allocation, and improved financial outcomes.

5.2.2 Machine Learning Models and Financial Decision-Making

The second objective of the study was to determine the effect of machine learning models on financial decision-making in manufacturing firms in Nairobi County. Descriptive results indicated that machine learning was highly rated for supporting investment decisions ($M = 4.10$, $SD = 0.30$), detecting financial anomalies early ($M = 4.10$, $SD = 0.30$), and improving the accuracy of financial analysis ($M = 4.01$, $SD = 0.44$). However, the use of machine learning for real-time decision-making was rated lower ($M = 3.02$, $SD = 1.09$), showing that firms face challenges in fully integrating ML into fast-paced financial contexts. Correlation analysis revealed a strong positive relationship between machine learning and financial decision-making ($r = 0.833$, $p < 0.01$). Regression analysis further confirmed its

significant effect ($\beta = 0.349$, $p < 0.001$), making it the strongest predictor among the AI dimensions studied.

These findings suggest that machine learning plays a central role in enhancing financial decision-making through anomaly detection, investment planning, and improved financial analysis. Although its use in real-time decisions remains limited, the results highlight the growing influence of machine learning as a strategic resource for data-driven financial management. Overall, machine learning models emerged as the most influential AI tool in this study, underscoring their potential to transform financial decision-making in manufacturing firms by strengthening analytical accuracy, risk management, and investment strategies.

5.2.3 Automated Financial Reporting and Financial Decision-Making

The third objective of the study was to establish the effect of automated financial reporting on financial decision-making in manufacturing firms in Nairobi County. Descriptive results showed that automation was strongly associated with improving financial transparency ($M = 4.10$, $SD = 0.30$) and real-time accessibility of reports ($M = 4.10$, $SD = 0.30$). Respondents unanimously agreed that automation reduces reporting errors and ensures consistent report generation ($M = 4.00$, $SD = 0.00$). Correlation analysis indicated a strong positive and significant relationship between automated financial reporting and financial decision-making ($r = 0.709$, $p < 0.01$). Regression analysis confirmed its significant contribution ($\beta = 0.206$, $p < 0.001$), although its effect was weaker compared to predictive analytics and machine learning.

These findings suggest that automated financial reporting enhances decision-making by improving accuracy, reliability, and timeliness of financial information. By reducing errors and increasing transparency, automation ensures that managers have

dependable data for budgeting, cost control, and risk assessment. Although its effect is not as strong as predictive analytics or machine learning, automation remains an essential tool in strengthening decision-making processes, particularly in environments where efficiency and compliance are critical.

5.2.4 Natural Language Processing Tools and Financial Decision-Making

The fourth objective of the study was to examine the effect of natural language processing tools on financial decision-making in manufacturing firms in Nairobi County. Descriptive findings indicated strong agreement that NLP enhances interpretation of policy documents ($M = 4.10$, $SD = 0.30$), improves understanding of complex financial texts ($M = 4.00$, $SD = 0.00$), and supports summarization of financial reports ($M = 4.00$, $SD = 0.00$). However, the ability of NLP tools to analyze financial documents faster was rated moderately ($M = 3.51$, $SD = 0.67$). Correlation analysis showed a moderate but significant relationship between NLP and financial decision-making ($r = 0.552$, $p < 0.01$). Regression analysis confirmed its positive and significant effect ($\beta = 0.128$, $p = 0.001$), though weaker compared to the other AI dimensions.

These findings suggest that NLP tools contribute to financial decision-making by simplifying complex financial information, enhancing report interpretation, and providing quick access to insights from unstructured data. Although its influence is less pronounced compared to predictive analytics, machine learning, and automation, NLP remains valuable in improving comprehension and reducing cognitive load in financial analysis. The results indicate that NLP is an emerging tool whose adoption and integration could further strengthen decision-making effectiveness in manufacturing firms as digital transformation advances.

5.3 Conclusions

This section presents the conclusions of the study drawn from the analysis of results in line with the specific objectives. Each conclusion highlights the extent to which the dimensions of artificial intelligence—predictive analytics, machine learning models, automated financial reporting, and natural language processing tools—influence financial decision-making in manufacturing firms in Nairobi County.

5.3.1 Predictive Analytics and Financial Decision-Making

The study concluded that predictive analytics has a significant positive effect on financial decision-making in manufacturing firms in Nairobi County. By enhancing budgeting accuracy, improving forecasting, and supporting resource allocation, predictive analytics enables managers to make informed and data-driven decisions. Although its application in risk anticipation was found to be moderate, the overall evidence indicates that predictive analytics is a critical tool for strengthening financial decision-making processes, making it indispensable for firms seeking efficiency and strategic foresight.

5.3.2 Machine Learning Models and Financial Decision-Making

The study concluded that machine learning models have a significant and positive effect on financial decision-making in manufacturing firms in Nairobi County. Machine learning emerged as the most influential AI dimension, particularly in enhancing investment planning, anomaly detection, and the accuracy of financial analysis. Although adoption for real-time decision-making remains limited, the findings demonstrate that machine learning provides firms with a strategic capability to improve analytical rigor and strengthen data-driven financial decisions.

5.3.3 Automated Financial Reporting and Financial Decision-Making

The study concluded that automated financial reporting significantly improves financial decision-making in manufacturing firms in Nairobi County by enhancing accuracy, timeliness, and transparency of financial information. By reducing errors and ensuring consistency in reporting, automation provides managers with reliable data for budgeting, cost control, and risk assessment. Although its effect was weaker compared to predictive analytics and machine learning, automation remains a vital enabler of efficient and accountable financial decision-making processes.

5.3.4 Natural Language Processing Tools and Financial Decision-Making

The study concluded that natural language processing tools have a positive and significant effect on financial decision-making in manufacturing firms in Nairobi County, though their influence is comparatively weaker than other AI dimensions. NLP enhances the interpretation of complex financial texts, improves policy document analysis, and supports report summarization, thereby reducing cognitive load and aiding decision-making. While adoption remains moderate in some areas such as document analysis speed, the findings highlight NLP's growing potential as an important tool for strengthening financial decision-making in the sector.

5.4 Recommendations of the Study

Based on the findings, the study recommends that manufacturing firms in Nairobi County increase their investment in predictive analytics to strengthen financial forecasting and budgeting processes. Firms should prioritize integrating predictive tools into their decision-making frameworks and train finance teams to use them effectively for risk anticipation. By doing so, firms can move beyond reactive decision-making to more proactive strategies,

thereby enhancing efficiency in resource allocation and improving resilience in uncertain financial environments.

The study also recommends that firms adopt and scale up the use of machine learning models, given their demonstrated strong influence on financial decision-making. Managers should leverage ML to improve anomaly detection, investment planning, and financial analysis accuracy. To address the observed gap in real-time application, firms should enhance their digital infrastructure and build capacity among finance teams to interpret and apply ML outputs effectively. This will help firms to respond quickly to dynamic financial conditions and create a sustainable competitive advantage.

In relation to automated financial reporting, the study recommends that firms continue expanding automation systems to ensure accuracy, transparency, and timeliness of financial information. Managers should prioritize automation not only for compliance purposes but also as a strategic tool for supporting budgeting, cost control, and risk assessment. To ensure uniform benefits across firms, especially SMEs, industry associations and policymakers could provide incentives and technical support to enhance the adoption of automation tools within the manufacturing sector.

Finally, for natural language processing tools, the study recommends that firms strengthen their adoption to better exploit their potential in interpreting complex financial documents, summarizing reports, and analyzing unstructured financial data. While current application levels remain modest, firms should invest in NLP solutions tailored for finance functions and provide training to decision-makers on their effective use. By doing so, NLP tools can reduce cognitive load on managers, speed up analysis, and enhance confidence in decision-making, particularly in high-stakes financial planning and risk assessment contexts.

5.5 Research Areas for Further Studies

Future research could broaden the scope by examining the influence of artificial intelligence on financial decision-making across different sectors beyond manufacturing, such as banking, healthcare, agriculture, or government agencies. This would provide comparative insights on how sectoral dynamics, regulatory environments, and resource capacities shape the effectiveness of AI adoption in financial management. Such cross-sectoral studies would enrich the generalizability of findings and help identify sector-specific best practices.

There is also need for studies that adopt a longitudinal research design to track how AI integration affects financial decision-making over time. Since this study applied a cross-sectional approach, future research could explore the evolution of AI adoption and its impact on financial strategies in response to technological advancements, regulatory changes, and shifts in economic conditions. This would provide a more dynamic understanding of how firms adapt and sustain decision-making effectiveness in changing environments.

Further studies could also explore behavioral and cognitive dimensions of AI adoption in financial decision-making. While this study concentrated on outcomes such as budgeting, investment planning, cost management, and risk assessment, future work could investigate how finance professionals' perceptions, attitudes, and levels of digital literacy influence the adoption and use of AI tools. Qualitative approaches, including interviews and case studies, would provide deeper insights into the human factors that shape the success or limitations of AI in decision-making contexts.

Lastly, future research could expand geographically to include comparative studies across countries or regions, especially within East Africa or other developing economies.

Since most AI research remains concentrated in developed contexts, examining adoption in resource-constrained environments would shed light on contextual barriers, opportunities, and policy implications. Such studies could also explore how national policies, infrastructure investments, and institutional support affect the role of AI in financial decision-making across diverse economic landscapes.

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APPENDICES

Appendix I: Introduction Letter

April 2025

Peter Mutua Kituu

Masters Student

KCA University

RE: REQUEST FOR RESEARCH DATA

I am undertaking a degree in Master of Business Administration at KCA University, and I am expected to submit a research paper on **"artificial intelligence and financial decision-making in manufacturing firms in Nairobi County, Kenya"** as part of my course work**.** To accomplish this, your company has been chosen to collect the data needed for this research. Your name will not be included in the research, and this info will be used solely for academic purposes. The research conclusions will be made availed on demand.

Kind regards.

Peter Mutua Kituu

Masters Student – Researcher

KCA University

Appendix II: Questionnaire

This questionnaire has been developed to collect information on the effect of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya. Kindly take the time to carefully read the questions and provide the best insight you can. Only scholarly purposes will be served by the information acquired.

Instructions

Pick only a response (box) for every question.

PART A: BACKGROUND INFORMATION

1. Kindly indicate your gender

   a) Male ( )

   b) Female ( )

2. Please indicate your age

   (a) Below 30 years ( )

   (b) Between 31-40 years ( )

   (c) Between 41-50 years ( )

   (d) Above 50 years ( )

3. How long have you been in your current position?

   a) Less than 1 year ( )

   b) Between 2-3 years ( )

   c) Between 4-5 years ( )

   (d) More than 5 years ( ).

4. Please indicate the highest level of education

   (a) Diploma ( )

   (b) Undergraduate Degree ( )

   (c) Master's Degree ( )

   (d) PhD ( )

PART B: ARTIFICIAL INTELLIGENCE

This part has four sections: predictive analytics, machine learning models, automated financial reporting and natural language processing tools.

Predictive Analytics Practice

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

Statement	**1**	**2**	**3**	**4**	**5**
Our firm uses predictive analytics to improve financial forecasting.					
Predictive tools help us anticipate future financial risks.					
Predictive analytics enhances our budgeting accuracy.					
We rely on data trends to guide financial planning.					
Predictive models assist in setting financial targets.					
The finance team regularly uses forecasting software.					

Machine Learning Models Practice

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

Statement	**1**	**2**	**3**	**4**	**5**
We use machine learning to support investment decisions.					
ML models help detect financial anomalies early.					
Our financial strategies are driven by algorithmic insights.					
Machine learning improves the accuracy of financial analysis.					
We have adopted ML for real-time financial decision-making.					
Our team is trained to interpret machine learning results.					

Automated Financial Reporting Practice

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2|Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

Statement	1	2	3	4	5
Our financial reports are generated using automation tools.					
Automation reduces reporting errors in our firm.					
Automated systems have improved reporting timeliness.					
We use software to compile monthly financial statements.					
Automated reporting has improved financial transparency.					
Financial reports are accessible in real-time through our systems.					

Natural Language Processing Tools Practice

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2|Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

Statement	1	2	3	4	5
NLP tools help us analyze financial documents faster.					
Our firm uses NLP to extract key financial insights.					
Sentiment analysis supports financial decision-making.					
We rely on NLP to summarize financial reports.					
NLP improves understanding of complex financial texts.					
NLP tools enhance our interpretation of policy documents.					

PART C: FINANCIAL DECISION-MAKING

To what magnitude do you concur with the following assertions? Rate in a scale of 1 to 5 (1 Strongly disagree, 2|Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree)

Component	1	2	3	4	5
Our financial decisions are data-driven and timely.					
We allocate financial resources efficiently.					
Investment planning is based on accurate forecasts.					
We have effective strategies for cost management.					
Risk assessments guide our financial decisions.					
Financial decisions support our firm's long-term goals.					

THANK YOU

Appendix III: Ethical Clearance Request Form

RESEARCH, INNOVATION, AND OUTREACH DIVISION

KCA UNIVERSITY SCIENTIFIC AND ETHICS REVIEW COMMITTEE

REQUEST FOR ETHICAL REVIEW FORM

The request must include the following information for the research to be considered for approval:

Name, institution, and contact details (email and phone number) of the principal/lead investigator/researcher:	Peter Mutua Kituu KCAU 2103562@students.kcau.ac.ke 0726 417 011
If it is a thesis, include also the name(s), institution(s), and contact details (emails and phone numbers) of the supervisor(s):	Supervisor: Dr. Brigitte Okonga-Wabuyabo dokonga@kcau.ac.ke
Date of request:	08/05/2025
Title of the Research:	Effect of artificial intelligence on financial decision-making in manufacturing firms in Nairobi County, Kenya
Planned or confirmed source of funding:	Personal funding
Members of the research group and their roles in the implementation of the study, as well as possible cooperation with other universities, research institutes, or similar organizations:	Peter Mutua Kituu being the principal researcher mandated with steering the study design, data collection, analysis and dissertation findings reporting lead person. As requirement for the award of MBA in KCAU, the study will not involve corporation with other universities or research institutes. Finance managers of manufacturing firms in Nairobi County, Kenya will however be involved in offering insights through structured questionnaire on how their organizations regard artificial intelligence and financial decision-making. KCAUSERC-Ethical review and approval

What is the level of risk presented by your research?	Please indicate whether the research budget implementation (Check risk document) stated on the application is: ✓ **Low risk** ☐ **Low risk** (*Research has no foreseeable risk of harm, discomfort, or inconvenience to respondents*) ☐ **Medium risk** (*Research has potential risk of unexpected negative consequences, harm or discomfort, but where appropriate steps can be taken to mitigate the risk*) ☐ **High risk (***Research with real and foreseeable risk of harm and discomfort to participants and or the research team, and which may lead to serious adverse consequences if these risks are not managed in a responsible manner. It involves highly sensitive topics and/or the participation of very vulnerable and marginalized individuals/groups*)
Would you like to bring any aspects of the applications to the Ethics Review Committee's attention?	**Please indicate them here** Voluntary participation: All respondents will voluntarily participate, with the right to withdraw at any time without consequences Confidentiality: The respondents will be anonymous and no personally identifiable information will be published or disclosed. Minimum risk: There are no anticipated physical or psychological risk associated with this research. Data security: Data will be stored securely and only used solely for academic purposes
What research data will be collected?	Primary data through questionnaires
What personal data and confidential information will be processed?	Personal data Participants gender, age, years of service in their position, personal or job emails Confidential information Head of finance or their equivalent response regarding artificial intelligence and financial decision-making in their corporations

Specify any special category or sensitive data that will be collected (tick all that apply)	☐ Ethnicity ☐ Mental Health (status, medical records conditions, to include disability) ☐ Physical Health (status, medical records conditions, to include disability) ☐ Sexual Orientation/Sexual life ☐ Genetic Data (to include DNA data) ☐ Biometric data (such as facial scan, iris scan, or fingerprint data used to identify a participant) ☐ Political opinions ☐ Trade Union membership ☐ Religious or philosophical beliefs ☐ Criminal Convictions and offences (to include alleged offences and convictions) ✓ ☐ None ☐ Other – Please specify below
How will data be stored and transferred during the research?	Password protected files to prevent unauthorized data access
Specify who will be able to access the identifying information and how you will ensure they process the information securely	Peter Mutua Kituu, the principal researcher. I will use code for the identifying information during analysis to ensure confidentiality. Data will be stored in password protected files during analysis to ensure confidentiality and will be disposed 1 year after dissertation completion in compliance with the ethical research guidelines
How will research data be preserved and shared on completion of the project? (NB: *Enter N/A in this section unless results will be published*)	N/A
Describe the measures that will be taken to ensure data are suitable for sharing, e.g., securing consent, anonymizing data prior to deposit/sharing, and sharing confidential or high-risk information using a controlled access repository.	All participants will be required to provide informed consent before participating in the study. Any identifying information such as job titles, gender or age will be coded before data analysis. Data will be aggregated, ensuring individual responses cannot be traced to specific participants
State how long you plan to retain personal data and any confidential information after the end of the project. Indicate also how the data will be disposed	One year after completion of the study Identifying and confidential information for the participants will be permanently deleted after the one-year period

As the Principal Investigator of this study, I declare that I take full responsibility for the proposed study and will conduct it according to the documented proposal and in line with KCAUSERC ethical guidelines.

By signing this document, I agree that:

a) All documents submitted with this application are true representations of the

study and have not been falsified.

b) This study will not commence in any way, and no participant will be recruited until final official approval is received from KCAUSERC
c) The study will be conducted according to the protocol submitted. All participants will be recruited and consented to according to the protocol.
d) Any protocol deviations or protocol violations to the submitted study must be reported to KCAU in writing by email to KCAUSERC immediately. Within five (5) business days of the deviation or violation, the Deviation/Violation Must be reported to the ISERC office.
e) Any study-related unexpected or serious adverse event must be reported to the ISERC Office by email within twenty-four (24) hours after the PI becomes aware of the event.

…….

……..

Principal Investigator's Signature **Date**

INFORMED CONSENT FOR RESEARCH PARTICIPATION

Introduction
You are invited to participate in a research study. This document provides information about the study so that you can make an informed decision about your participation. Please take the time to read the information below. If you have any questions, feel free to ask the researcher.

Purpose of the Study
The purpose of this study is to examine how the adoption of artificial intelligence (AI) tools—specifically predictive analytics, machine learning models, automated financial reporting, and natural language processing—affects financial decision-making in manufacturing firms within Nairobi County, Kenya. As a finance professional in your organization, your insights are vital in helping the researcher understand how these technologies are applied in real-world decision-making processes such as budgeting, investment planning, cost management, and risk assessment. The findings will contribute to academic knowledge and provide practical recommendations to help manufacturing firms optimize their financial strategies through AI integration. Your responses will be treated with strict confidentiality and used solely for academic purposes.

Study Procedures
If you agree to participate, you will be asked to offer response by providing primary data via structured questionnaire response targeting finance managers among manufacturing firms in Nairobi County. The study is expected to be completed within a three-month period.

Potential Risks and Discomforts
There may be some risks associated with participation in this study.

As at now, there are no foreseeable risk or discomfort to this study participants. Every effort will be made to minimize potential risk that may arise, and you can withdraw from the study at any time without penalty.

Potential Benefits
While participating may not directly benefit you, the results of this study may contribute to design frameworks that improve the financial decision-making in manufacturing firms within Nairobi County, Kenya.

Confidentiality
Your participation will be kept confidential. Any data collected will be stored securely and only accessible to the research team. Your identity will not be revealed in any publication or presentation resulting from this research.

Voluntary Participation
Participation in this study is completely voluntary. You have the right to withdraw from the study at any time without any negative consequences or loss of benefits to which you are otherwise entitled.

Questions
If you have any questions about this study, your participation, or your rights as a participant, please contact the principal investigator at [*2103562@students.kcau.ac.ke*].

Consent
By signing below, you indicate that you have read the information provided above, understand the purpose and procedures of the study, and voluntarily agree to participate. You can withdraw from the study at any time without penalty.

Participant Statement:

I, the undersigned, consent to participate in this study.
Name of Participant: _____
Signature of Participant: _____
Date: _____

Researcher (Principal Investigator –P1) Statement:

I, the undersigned, confirm that I have explained the nature of this study to the participants, answered all questions, and ensured that they understand the information provided.

Name of Researcher: Peter Mutua Kituu

Signature of Researcher: ……

Date: **08/05/2025**

Appendix IV: Ethical Approval

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Website: www.kca.ac.ke

KCA UNIVERSITY SCIENTIFIC & ETHICS REVIEW COMMITTEE

REF: **KCAU/SERC/ SOB0209** **Date: 21ST JULY 2025**

TO: **PETER MUTUA KITUU (21/03562)**

Dear Sir/Madam,

RE: ARTIFICIAL INTELLIGENCE AND FINANCIAL DECISION-MAKING OUTCOME IN MANUFACTURING FIRMS IN NAIROBI COUNTY, KENYA

This is to inform you that KCA University Scientific Ethics Review Committee (KCAUSERC) has reviewed and approved your above research proposal. Your application approval number is ***KCAUSERC/SOB0209.*** The approval period is ***21st July 2025 – 21st July, 2026.***
This approval is subject to compliance with the following requirements;

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

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

Yours sincerely

Dr. Caroline Ntara
Chairperson
KCA University Scientific & Ethics Review Committee

Appendix V: NACOSTI Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **679202**

Date of Issue: **27/August/2025**

RESEARCH LICENSE

This is to Certify that Mr.. Peter Mutua Kituu of KCA University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: ARTIFICIAL INTELLIGENCE AND FINANCIAL DECISION-MAKING OUTCOME IN MANUFACTURING FIRMS IN NAIROBI COUNTY, KENYA for the period ending : 27/August/2026.

License No: **NACOSTI/P/25/4178773**

679202

Applicant Identification Number

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

Verification QR Code

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

See overleaf for conditions