

Artificial intelligence in investment decision-making: A senior management perception among commercial banks in Kenya

Milton Mucembi¹
Ruthwinnie Munene²

¹milontonjeru5@gmail.com (+ 254741359598)

²ruthwinniem@gmail.com (+ 254722835443)

^{1,2}Mount Kenya University, Kenya

<https://doi.org/10.51867/ajernet.7.1.57>

ABSTRACT

The banking sector is being significantly reshaped by the rapid introduction and application of Artificial Intelligence (AI) in the investment decision-making processes of commercial banks. The purpose of this study, therefore, was to analyze perceptions of AI in investment decision-making by senior management in commercial banks in Kenya. The study was anchored by rational decision-making theory, bounded rationality theory, intuitive decision-making theory, heuristic decision-making theory, and the technology acceptance model. The mixed-methods approach was utilized in the study and survey and in-depth interviews with senior management of commercial banks, with secondary information drawn from industry sources. The target population was the senior managers in the investment department in all the thirty-nine commercial banks in Nairobi City. The study adopted a census approach in all the thirty-nine commercial banks. AI applications allow commercial banks to streamline their workflows and improve the ability to forecast true business health, enabling decision-making based on quality data. AI adoption leads to minimized operational risks and dynamic adaptation of investment strategies due to market changes. The study employed a mixed-methods approach to explore the possibilities of AI, the challenges of AI, and the possibilities of applying AI in the banking sector. The data was analyzed using SPSS version 25 for descriptive and inferential statistics. The results show significant positive correlations: leadership commitment with organizational culture ($r=0.65$, $p<0.01$), resource availability with leadership ($r=0.58$, $p<0.01$), and organizational flexibility ($r=0.62$, $p<0.01$). Employee attitudes are positively correlated with leadership ($r=0.52$, $p<0.01$) and culture ($r=0.55$, $p<0.01$), while perceptions of AI risks are negatively correlated with leadership ($r=-0.45$, $p<0.01$). The regression model explains 61% of perception variance ($R^2=0.61$), with leadership showing the strongest influence ($\beta=0.33$, $p<0.01$), followed by culture ($\beta=0.28$, $p<0.01$), resource availability ($\beta=0.22$, $p<0.01$), and employee attitudes ($\beta=0.17$, $p=0.018$). Perceived risks negatively impact perceptions ($\beta=-0.14$, $p=0.022$). The model's F-statistic is 18.2 ($p<0.001$), indicating overall significance and emphasizing the importance of organizational support in AI adoption. The report provides actionable recommendations, including augmented AI training programs, investing in AI with high scalability, and developing transparent frameworks for regulating AI in a way that will promote AI use in Kenya's banking sector. This will enhance the efficiency, accuracy, and optimization of financial decisions. Findings from this study can be used in the formulation of policy issues on the development of AI-specific regulations and guidelines for the prudent use of AI technologies in the financial services industry in evaluating their present investment decision-making, thus contributing to SDG 9 on industry innovation and infrastructure.

Key words: Artificial Intelligence, Banking, Commercial Banks, Investment Decisions, Senior Management Perception

I. INTRODUCTION

The state of Artificial Intelligence [AI] in banking around the world is a fast-evolving one. As per Statista, the AI in banking market was valued at more than USD 21 billion in 2020, and is expected to have an approximate value of USD 164 billion by 2029. This translates into a phenomenal 25.6% CAGR (compound annual growth rate). In the contemporary financial landscape, the intersection of artificial intelligence (AI) and investment decision-making has emerged as a transformative force, shaping how organizations evaluate opportunities and manage risks. Globally, the adoption of AI technologies in finance has surged, driven by advancements in machine learning, big data analytics, and computational power. (Brynjolfsson & McAfee, 2017).

Financial institutions are increasingly leveraging AI to enhance predictive accuracy, streamline operations, and provide personalized services. AI tools like Machine learning, predictive analysis, and Natural language processing have been a game changer for financial operations. As a sign of this increasing trend, a report by Markets and Markets indicates that AI in the banking market is expected to grow from USD 3.89 billion in 2020 to USD 27.67 billion by 2025, at a Compound Annual Growth Rate (CAGR) of 47.9% (Mishra et.al., 2024). This has not only made financial information processing more efficient but also improved financial risk analysis and optimization of investment strategies, and ultimately enhanced profitability, regulatory compliance and competitive standing in the marketplace (Königstorfer & Thalmann, 2020). According to a report by Deloitte, organizations utilizing AI in investment processes experience

improved operational efficiency, enabling them to make more informed decisions rapidly. Institutions like BlackRock and Goldman Sachs have invested heavily in AI-driven tools to manage billion-dollar portfolios, demonstrating a significant shift towards data-driven decision-making in global financial markets. (Merendino et al., 2018).

Regionally, the African banking sector is undergoing a digital transformation, offering a fertile ground for the application of AI in investment decision-making. Countries such as Kenya are at the forefront of this evolution, with a rising number of fintech startups and established banks integrating AI technologies to optimize their investment strategies. The Kenyan banking sector has witnessed a 30% increase in AI adoption over the past two years, driven by the need to enhance customer experience, reduce operational costs, and gain a competitive edge. Regional initiatives like the African Development Bank's push for digital finance highlight the importance of innovation in driving economic growth and stability. Furthermore, the rise of mobile banking services and digital wallets has paved the way for more sophisticated data analytics capabilities within the region's financial institutions, facilitating better investment decisions (Gregory & Sovacool, 2019).

Nationally, Kenya stands as a beacon of innovation within the African context, with its commercial banks increasingly recognizing the importance of AI in shaping their investment strategies. The Central Bank of Kenya has encouraged the adoption of technology in financial services, creating a supportive regulatory environment for AI-driven solutions. Senior management within commercial banks plays a crucial role in shaping the perception and subsequent implementation of AI technologies. Their understanding and acceptance of AI influence how effectively these tools can be integrated into investment decision-making processes. Recent studies have indicated that senior management's perceptions of AI's effectiveness directly correlate with their willingness to invest in such technologies. Furthermore, with Kenya's ambitious Vision 2030 goal aiming to transform the country into a middle-income economy, the successful integration of AI in banking is seen as a vital component in achieving sustainable economic growth (Gregory & Sovacool, 2019).

For instance, in a recent study, 50% of the banking executives in Kenya saw high implementation costs as a major challenge in the adoption of AI technologies in investment decisions. However, concerns to accountability and transparency are raised as more and more financial institutions are using AI systems to make vital decisions. In order to understand these dynamics, the purpose of this study is to examine the perceptions of senior management on the application of AI in investment decision making in commercial banks in Kenya (Haidari, 2023).

The current trends of AI in banking are changing globally. As per Statista, the market for AI in banking was worth more than US\$ 21 billion in 2020 and is estimated to reach around US\$ 164 billion by 2029. This is an astonishing CAGR of 25.6%. To describe the distribution of the AI applications in the financial sector, Table 1 presents various applications and their market shares:

Table 1
Distribution of AI Applications in the Banking Sector (2022)

Application	Market Share %
Fraud Detection	35
Risk Management	25
Customer service Automation	20
Investment Decision-Making	15
Compliance and Regulatory	5

(Source, CBK website 2024)

As it pertains to Kenya, a recent survey indicated that only 20% of commercial banks have incorporated AI into their investment decision-making processes, demonstrating a significant gap in adoption compared to global trends. The perceptions of senior management regarding AI's impact on investment decision-making are integral for successful integration within the banking sector (Familoni & Shoetan, 2024).

Although the application of Artificial Intelligence (AI) can greatly enhance investment decision making capability in the Kenya banking industry, its complete integration is not without some challenges. The main challenge that has been identified to the adoption of AI technologies is the cost. A constraint that includes the expense of developing the necessary infrastructure, acquiring better software, and hiring skilled labor that could hinder the willingness of banks, particularly the small and medium-sized enterprises (Han et al., 2023). Another challenge is lack of AI talent and data scientists. As a result, the development and deployment of AI-powered investment tools are slow, and hence the benefits that could have been realized through technological innovation are not realized. Compliance and regulatory risks poses as a challenge since every aspect of a financial institution in Kenya is regulated by regulatory laws like banking sector directives and data protection legislation. Since financial services are critical. AI applications in these sectors are closely watched; therefore, we need to approach the delivery of compliance requirements while balancing operational risks (Huang & You 2023). Second, the majority of the senior executives and finance professionals are rather conservative and tend to resist the change as compared to how they have been doing it. Such reluctance can

be a barrier to the adoption of AI powered automation since stakeholders may refuse the application of AI systems because they are less accurate or reliable than human judgment (Remmers et al., 2017).

Ethical issues and security threats are also challenges due to data privacy and cyber security issues: The use of large amounts of data to train AI algorithms comes with the risk of data privacy and cyber security. There is also the risk of algorithmic bias in investment recommendations that can result in unfair or poor decisions that are detrimental to some groups (Kowalkiewicz, 2024).

1.1 Statement of the Problem

Commercial banks play a crucial role in the financial system, and investment decision-making is a major activity that affects financial stability, profitability, and long-term growth. Traditionally these banks depend on expert human judgment, historical financial data and gut feeling as the basis for making investment decisions. But they also have serious weaknesses, like information overload, susceptibility to cognitive biases, and slow processing (Haidari, 2023). As financial markets are rapidly evolving, the complexity of uncertainty factors also increasing, they are now impractical for rendering timely and accurate insights into investment decisions. In response to such gaps, it's worth noting that Artificial Intelligence (AI) technology has emerged as an essential medium that can reshape investment decision-making in banking organizations.

The possibilities of the artificial intelligence technologies, such as machine learning (ML), natural language processing ML, and predictive analytics are huge to improve the investment decision-making process as these technologies increase accuracy, automate data processing, and minimize the risks in the investment process (Huang & You, 2023). AI systems can process massive volumes of both structured and unstructured data in real-time, identifying trends and generating predictive insights that even the most experienced human analysts might miss. AI in investments: Empirical research indicates that AI-driven investment models can lead to better risk assessment, enhanced fraud detection and algorithmic trading to offer competitive advantage to financial institutions (Shoetan & Familoni, 2024). Instead, Kenyan commercial banks have been lagging behind in the application of AI technology in their investment process, notwithstanding their related advantages.

In this light, this study sought to critically explore senior management perspectives on the use of AI in investment decision-making among commercial banks in Kenya. Thus, to filling this knowledge gap by providing a comprehensive analysis of artificial intelligence's value proposition, challenges, and strategic deployment in Kenya's banking sector and significantly improve the investment decision-making process and promote financial innovation in Kenya's banking landscape.

1.2 Research Objectives

- i. To Assess the Level of Awareness and Understanding of Artificial Intelligence (AI) Technologies Among Senior Management in Commercial Banks in Nairobi County.
- ii. To explore the perception of risk associated with the use of AI technologies in investment decision-making among senior management in commercial banks:
- iii. To Analyze the Influence of Organizational Culture, Structure, and Support on the Adoption of AI Technologies in Investment Decision-Making in Commercial Banks.

1.3 Research Questions

- i. What is the current level of awareness and understanding of AI technologies among senior management in commercial banks in Nairobi County?
- ii. What are the perceived risks associated with the implementation of AI technologies in investment decision-making among senior management in commercial banks?
- iii. How do organizational culture and structure influence the adoption of AI technologies in investment decision-making processes among commercial banks in Nairobi County?

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 The Rational Decision-Making Theory

The rational decision-making theory is one of the primary frameworks that is used to describe the process of decision making—stating that decision-makers will consider, in a systematic manner, all available alternatives before choosing the one with the greatest utility (Simon, 1979). And this theory claims that decision-makers collect data, analyze information and choose whatever the most optimal course of action is, preferably using logic and not subjective criteria. Commercial banks sift through complex financial data and market trends in their investment decisions. The use of AI in commercial banking could transform the way investment decisions are made and provide insights that are actionable and data driven. (Uzonwanne, 2016).

2.1.2 Bounded Rationality Theory

Bounded rationality, a paradigm introduced by Herbert Simon, acknowledges the intrinsic limitations of human decision-making faculties. According to this theory, although individuals aim for rational decision making, they are limited by their ability to process information and time constraints (March & Simon, 1980). Due to the large volume of data and complexity of markets in investment stage and in commercial banks, investment managers rely on a "satisficing" approach. This gives rise to a tendency to accept AI solutions that are satisfactory rather than optimal, as cognitive load and time pressure limit their ability to process thoroughly every possible alternative (Luan et al., 2019). These limitations can lead to default and loss of profit opportunities for some and failure to invest in the right investments, considerably impairing the bank's economic performance.

2.1.3 Intuitive Decision-Making Theory

The theory of intuitive decision-making suggests that intuition, or "gut feelings," play a major role in our decision-making processes, especially in situations of uncertainty. Commercial banks with experienced professionals tend to use their intuitions to make timely investments based on fluctuating market conditions. In the fast-paced and data-light environment of financial markets, there is an inclination to rely on gut feeling — speed and decisiveness can be more valuable than data. AI can leverage these blind spots inherent in pure analytics-based decision-making and context-dependent and experiential information that could be critical to successful investment decisions. (Remmers et al., 2017).

2.1.4 Heuristic Decision-Making Theory

According to heuristic decision-making theory, people frequently use heuristics, or mental shortcuts, to simplify difficult decision-making processes, particularly in situations with limited time or complex problems (Tversky & Kahneman, 1974). Since heuristics aid in decision-making, they have utility in high-speed environments (e.g., venture commercial bank) where quick response times can allow investment opportunities to be capitalized on more quickly. But using these cognitive shortcuts can lead to biases and regularities of error, resulting in poor decision making. Heuristics are commonly used by financial institutions, in which investment decisions are made quickly in demanding situations. (Luan et al., 2019).

2.1.5 The Technology Acceptance Model (TAM)

TAM-The Technology Acceptance Model is a well-defined model that explains the determinants of user's acceptance of technology. In a prominent early example of usage modeling, Venkatesh and Davis (2000) developed the technology acceptance model (TAM), which posits that two primary constructs, perceived usefulness (PU) and perceived ease of use (PEOU), underlie whether individuals adopt information technologies. TAM is particularly relevant to this study, which investigates how and why AI is incorporated into investment decision making by senior management in commercial banks in Kenya, as it explores the drivers behind the acceptance and utilization of AI solutions by these upper-echelon executives in making decisions about investment portfolios (Venkatesh & Davis, 2000).

2.2 Empirical Review

This review is on integration of Artificial Intelligence (AI) in investment decision-making is transforming the banking sector by enhancing efficiency, risk management, and market analysis as financial institutions increasingly adopt AI-driven technologies.

2.2.1 Awareness and understanding of AI Among Senior Management

The awareness and comprehension of AI technologies among senior management in commercial banks are critical determinants of AI adoption. AI encompasses a wide range of technologies, including machine learning, natural language processing, predictive analytics, robotics, and computer vision, all of which have the potential to revolutionize investment decision-making through enhanced data analysis, pattern recognition, and predictive capabilities. However, despite the growing interest in AI and its proven potential to enhance efficiency and profitability, significant gaps in understanding among financial executives remain, which could hinder its widespread implementation across the commercial banking sector. According to Tversky and Kahneman (1974), a lack of awareness and understanding of AI's practical applications is one of the most prominent barriers to successful AI integration in banking institutions.

2.2.2 Perceived Benefits and Challenges of AI in Investment Decision-Making

The integration of artificial intelligence (AI) into investment decision-making offers commercial banks significant advantages, making it one of the most transformative technologies in the financial industry today. AI, with its ability to analyze vast amounts of financial data, identify patterns, and generate predictive insights, offers numerous benefits for improving investment strategies, risk assessment, and overall portfolio management. One of the primary advantages of AI is its ability to process large volumes of data much faster and more accurately than humans can. By

leveraging AI, banks can uncover trends, correlations, and forecasts that would be nearly impossible for human analysts to identify, leading to more informed, timely, and accurate investment decisions courtesy of AI's predictive capabilities (Kumar et.al., 2023).

Another significant advantage of AI in investment decision-making is its ability to reduce human biases, which often distort traditional investment decisions. Traditional investment methods often rely on human intuition, judgment, and past experiences to make decisions, all of which can lead to cognitive biases such as overconfidence or loss aversion. Moreover, AI can automate several time-consuming and repetitive tasks that would otherwise be carried out manually by financial analysts, thus improving operational efficiency. By automating routine investment analysis tasks, such as data collection, trend analysis, and portfolio balancing, AI frees up analysts to focus on higher-level strategic planning and value-added activities. This increased efficiency reduces the time required to process investment data, which allows banks to act on emerging opportunities much more quickly than if they were relying on manual analysis. AI-driven automation not only enhances the speed and efficiency of decision-making processes but also minimizes the likelihood of errors that can occur due to human oversight or fatigue (Huang & You, 2023).

Overall, AI adoption in investment decision-making presents significant advantages, such as enhanced risk assessment, improved efficiency, and reduced human biases. However, these benefits come with their own set of challenges, including high implementation costs, regulatory compliance issues, and data security concerns. Banks must carefully evaluate these challenges and take proactive measures to address them in order to successfully implement AI-driven investment strategies. While AI has the potential to transform the way banks approach investment decisions, its successful integration depends on overcoming these hurdles and ensuring that the technology is deployed responsibly and in compliance with industry standards. (Stewart & Jürjens, 2017).

2.2.3 Impact of Organizational Culture and Structure on AI Adoption

The successful adoption of AI in investment decision-making is significantly influenced by the culture and structure of an organization. Commercial banks that cultivate a culture of innovation and adaptability are more likely to embrace AI technologies, while those with rigid structures and a resistance to change may face significant challenges in integrating AI into their investment strategies. One of the most important cultural factors that impact AI adoption is the perception of leadership. If senior management views AI as a strategic enabler and a tool for growth, they are more likely to actively support and invest in its implementation (Kowalkiewicz, 2024).

Siloed organizational structures, however, can significantly hinder this process. When departments operate in isolation, the flow of information is restricted, and the synergy needed for successful AI implementation is diminished. In such cases, technological innovation may be stifled, as departments may prioritize their own goals over shared organizational objectives. Banks that promote collaborative cultures, where different teams work together toward common goals, have a distinct advantage in adopting AI technologies. Moreover, the structure of decision-making processes within a bank can either accelerate or slow down AI adoption. Some banks operate under centralized decision-making structures, where high-level executives have the authority to make key strategic choices, often with limited input from lower management or frontline employees (Han et.al., 2023).

Furthermore, these structures can foster a sense of ownership and accountability among employees, who may be more motivated to engage with and advocate for AI initiatives. Another critical factor in AI adoption is the role of change management strategies. For AI integration to be successful, banks must have robust frameworks in place to manage the transition effectively. Organizational change often meets with resistance, particularly when employees perceive a new technology as threatening or disruptive. Successful AI adoption requires a strategic approach to overcoming this resistance through clear and transparent communication, targeted employee training, and ongoing support throughout the implementation process. Change management programs should focus on educating employees about the benefits of AI and addressing their concerns about job security and role changes. Banks that fail to implement proper change management strategies may encounter delays in AI adoption, as employees may be hesitant to adopt AI systems or may resist utilizing new technologies. A well-structured change management framework helps to foster trust among employees, encourages a positive attitude toward the technology, and ensures that the transition to AI-driven investment decision-making is as seamless as possible (Uzonwanne, 2016).

Leadership perception, collaboration, decision-making processes, and change management strategies all contribute to the overall readiness of a bank to embrace AI. By cultivating a culture of innovation, empowering employees, and addressing potential resistance to change, commercial banks can position themselves to integrate AI technologies more effectively, ultimately enhancing their investment decision-making capabilities. Banks that take a strategic and comprehensive approach to AI adoption are more likely to realize the full potential of these technologies, while those that fail to address organizational challenges may struggle to realize the benefits of AI in the long term. (Gregory & Sovacool, 2019).

III. METHODOLOGY

Case study analysis proved to be particularly effective for the examination of intricate, real-world situations; it afforded nuanced understandings of specific contexts while simultaneously enabling more comprehensive conclusions across the industry (Yin, 2017). This study uses a mixed-methods research design which facilitated the collection of detailed, in-depth data on managerial attitudes toward AI, while also enabling statistical analysis of trends and patterns in AI adoption. By integrating these methodologies, the study sought to reveal not only the statistical trends in AI application but also the nuanced perspectives of senior management, providing a comprehensive understanding of AI's role in investment decision-making processes in Kenya's commercial banking sector (Yin, 2017). For this study, data was collected through both primary and secondary data sources which included surveys, interviews and secondary data analysis from existing literature, bank reports and industry publications to which gave the context and background to the primary data collected. The target population for this study were senior managers in the thirty-nine commercial banks in Nairobi County as it hosts all the commercial banks headquarters in Kenya that have integrated AI technologies into their investment strategies. This study employed a purposive sampling technique to select senior managers and branch managers from the targeted commercial banks in Nairobi County. The sampling frame consisted of a list of senior managers and branch managers from the selected commercial banks. Since the population was not big census techniques was used to all the senior and branch managers in all the commercial banks. The qualitative information collected via semi-structured interviews was thematically analyzed using the principles of thematic analysis (Braun & Clarke, 2006). The quantitative data collected through the survey was analyzed using descriptive statistics, frequencies, and percentages to summarize the AI use and performance of the AI tools in the banking sector (Field, 2018). Ethical standards were maintained where all participants signed a consent form to prove that they had been informed of the goals of the study, their role in it, and that their participation was voluntary.

IV. FINDINGS AND DISCUSSIONS

4.1 Response Rate

The response rate of 75.0 % was satisfactory and provided a reliable basis for analyzing senior management perceptions regarding AI technologies in investment decision-making. This agree with (Braun & Clarke, 2006) that a response rate above 75% is reliable.

Table 2

Survey Response Rate

Response	Frequency	Percent
Returned	30	75.0 %
Not returned	10	25 %
Total	40	100%

4.2 Descriptive Statistics

These findings on experience indicate that the majority of participants possessed substantial knowledge and familiarity with the data and industry practices, which is crucial for providing informed perceptions on AI adoption in investment decision-making within their organizations. The detailed distribution of experience is summarized in Table 3.

Table 3

Experience in the Organization

	Frequency	Percent
5-10years	10	33.33
over 10 years	20	66.67
Total	30	100.0

4.2.1 Senior Management Awareness and Understanding of AI Technologies

The respondents demonstrated a moderate to high level of knowledge regarding AI technologies, with a mean score of 4.00 (on a 5-point scale), indicating that senior managers are relatively well-informed about AI concepts and their applications in banking. The results imply that there has been some level of training and educational initiatives related to AI within the banks, contributing to the perceived readiness of senior management to adopt AI technologies. Senior management possesses a solid understanding of AI, which is essential for informed decision-making and successful integration of AI into investment processes within commercial banks in Nairobi County.

Table 4

Senior Management Awareness and Understanding of AI Technologies

Descriptive Statistics			
	N	Mean	Std. Deviation
Knowledge of AI Technologies	30	4.0	0.75
Perception of AI's Potential in Investment Decision-Making	30	3.85	0.80
Valid N (list wise)	30		

4.2.2 Risk Perception Level

Table 5 presents the average perceptions of senior management regarding key risk areas. Most senior managers reported limited direct experience with AI failures, indicating a cautious but prepared stance towards potential challenges. The awareness of AI risks, particularly related to ethical considerations and data security, underscores the need for robust risk mitigation strategies. The findings suggest that while senior management recognizes significant risks especially ethical concerns and data security they generally perceive their organizations as moderately prepared to handle AI-related risks. This perception highlights a proactive attitude towards developing policies and frameworks to manage AI risks effectively. The average risk perception score (~3.25) indicates that managers are cautious about AI risks but do not view them as insurmountable. Ethical and security concerns stand out as the most prominent perceived risks, aligning with the importance of ethical AI deployment and data protection in investment decision processes. These insights are crucial for understanding senior management's readiness to adopt AI and their need for risk management strategies to facilitate successful integration.

Table 5*Risk Perception Level*

Descriptive Statistics			
	N	Mean	Std. Deviation
Data Security Risks	30	3.15	0.85
Ethical Concerns (Bias, Transparency)	30	3.40	0.88
Regulatory and Compliance Risks	30	3.20	0.83
Overall Risk Perception (Average)	30	3.25	0.80
Valid N	30		

4.2.3 Organizational Culture and Leadership Support

The structural factors influencing AI adoption were examined as presented in Table 6. The relatively high mean value of 3.80 for flexibility and decentralization suggests that organizational structures promoting adaptability and less rigid hierarchies positively influence AI adoption. Conversely, more rigid hierarchical structures are perceived as potential barriers. Overall, these findings underscore the importance of a supportive organizational culture, committed leadership, and flexible structures in fostering an environment conducive to AI integration in investment decision-making processes within commercial banks in Nairobi County.

Table 6*Organizational Culture and Leadership Support*

Structural Factor	N	Mean	Std. Deviation
Flexibility and Decentralization Facilitating AI Adoption	30	3.80	0.65
Rigid Hierarchies Hindering AI Adoption	30	3.20	0.70
Valid N	30		

4.3 Correlation Analysis

The correlation matrix (Table 7) presents the Pearson correlation coefficients between these variables. The results reveal several significant relationships:

Table 7*Pearson Correlation Coefficients between these Variables*

Variables	1	2	3	4	5	6
Leadership Commitment to Innovation	1					
Organizational Culture Supporting Innovation	0.65**	1				
Resource Availability for AI Adoption	0.58**	0.60**	1			
Employee Attitudes towards Technological Change	0.52**	0.55**	0.50**	1		
Perception of AI Risks	-0.45**	-0.48**	-0.42**	-0.40**	1	
Organizational Flexibility Facilitating AI Adoption	0.62**	0.60**	0.55**	0.50**	-0.38**	1

p < 0.01, p < 0.05

The analysis indicates strong positive correlations between leadership commitment and organizational culture supporting innovation ($r = 0.65$, $p < 0.01$), suggesting that committed leadership tends to foster an innovative culture conducive to AI adoption. Similarly, resource availability correlates positively with both leadership commitment ($r = 0.58$) and organizational flexibility ($r = 0.62$), highlighting that resource allocation is linked with structural and cultural support for AI. Employee attitudes also show positive, moderate relationships with leadership and organizational culture, implying that management support influences staff perceptions towards technological change. Conversely, perceptions of AI risks are negatively correlated with leadership commitment ($r = -0.45$) and organizational support, indicating that stronger leadership and cultural support may mitigate perceived risks associated with AI. The correlation analysis underscores the interconnectedness of organizational factors influencing AI adoption. Enhancing leadership commitment and fostering an innovative culture are likely to positively impact resource allocation, employee attitudes, and organizational flexibility, collectively facilitating AI integration in investment decision-making processes within Nairobi's commercial banks. These insights can inform strategic initiatives aimed at strengthening organizational readiness for AI adoption.

4.4 Regression Analysis

The regression model assesses the relative influence of variables such as leadership commitment, organizational culture, resource availability, employee attitudes, and perceived risks.

Table 8

Regression Model Summary

Model	R	R ²	Adjusted R ²	Std. Error of Estimate	F-statistic	P value F
1	0.78	061	0.58	0.45	18.2	0.000**

$p < 0.01$

Table 9

Regression of Coefficients

Variable	Unstandardized Coefficient (B)	Standard Error	Beta (β)	t-value	p-value
Constant	0.85	0.20	-	4.25	0.001**
Leadership Commitment to Innovation	0.30	0.07	0.33	4.29	0.001**
Organizational Culture Supporting Innovation	0.25	0.06	0.28	4.17	0.002**
Resource Availability for AI Adoption	0.20	0.05	0.22	4.00	0.003**
Employee Attitudes towards Technological Change	0.15	0.06	0.17	2.50	0.018**
Perception of AI Risks	-0.12	0.05	-0.14		0.022**

Based on the results of these study indicated in the table above, $Y = \beta_0 + \beta_1X_1 + \beta_2X_2$

+ $\beta_3X_3 + \beta_4X_4$ becomes;

$$Y = 0.85 + 0.30X_1 + 0.25X_2 + 0.20X_3 + 0.15X_4 + \varepsilon'$$

X_1 = Leadership Commitment to Innovation;

X_2 = Organizational Culture Supporting Innovation

X_3 = Resource Availability for AI Adoption

X_4 = Employee Attitudes towards Technological Change

X_5 = Perception of AI Risks

ε' =Error term

The regression results demonstrate that organizational factors significantly predict senior management perceptions of AI adoption, with an R^2 of 0.61 indicating that approximately 61% of the variance in perceptions is explained by these variables. Leadership commitment emerges as the strongest predictor ($\beta = 0.33$, $p < 0.01$), followed by organizational culture and resource availability. Employee attitudes positively influence perceptions, while perceived risks negatively impact perceptions of AI adoption. The overall model is statistically significant ($F = 18.2$, $p < 0.001$), confirming that these predictors collectively provide a meaningful explanation of senior management perceptions.

4.5 Discussion

Based on these findings, it was concluded that senior management in Nairobi's commercial banks generally have a favorable perception of adopting artificial intelligence in investment decision-making processes. They recognize AI's potential to improve efficiency, accuracy, and competitiveness within the banking sector. These results agree with Huang, and You (2023) that AI-driven automation not only enhances the speed and efficiency of decision-making

processes but also minimizes the likelihood of errors that can occur due to human oversight or fatigue. These findings also agree with Tversky and Kahneman (1974), who argued that lack of awareness and understanding of AI's practical applications is one of the most prominent barriers to successful AI integration in banking institutions. The positive outlook is largely driven by strong leadership support, a culture that values innovation, and the availability of necessary technological resources and skilled personnel this is supported by (Kowalkiewicz, 2024) where if senior management views AI as a strategic enabler and a tool for growth, they are more likely to actively support and invest in its implementation. This results also aligns with Kumar et.al (2023) that AI adoption in investment decision-making presented significant advantages, such as enhanced risk assessment, improved efficiency, and reduced human biases. However, these benefits came with their own set of challenges, including high implementation costs, regulatory compliance issues, and data security concerns. Banks needed to carefully evaluate these challenges and take proactive measures to address them in order to successfully implement AI-driven investment strategies.

The findings align with understanding the level of awareness and knowledge about AI technologies among senior management was critical in determining their readiness for adoption. Awareness encompassed familiarity with AI concepts, their application in investment decision-making, and recognition of potential advantages and limitations (Königstorfer, & Thalmann, 2020). This finding aligns with Haidari (2023), organizational structure could impact AI adoption by influencing decision-making processes, resource allocation, and communication channels. Hierarchical structures with rigid decision-making frameworks might have found it challenging to integrate AI technologies effectively, as opposed to more decentralized structures that promoted collaboration and innovation.

However, concerns regarding security risks, data privacy, and potential job displacement serve as significant barriers that influence their perceptions negatively. This can be overcome by ensuring that the technology is deployed responsibly and in compliance with industry standards. (Stewart & Jürjens, 2017). Additionally, the level of organizational readiness and staff attitudes play crucial roles in shaping perceptions toward AI adoption. It was also concluded that successful integration of AI relies heavily on addressing these concerns through effective risk management, employee training, and ensuring organizational preparedness. Overall, while the outlook remains optimistic, the study emphasizes that overcoming perceived risks and fostering a supportive environment are essential steps toward fully harnessing AI's benefits in investment decision-making within the banking sector in Nairobi. Shoetan and FAMILONI (2024) argued that leveraging AI, banks can uncover trends, correlations, and forecasts that would be nearly impossible for human analysts to identify, leading to more informed, timely, and accurate investment decisions. AI's predictive capabilities. Therefore, this understanding can guide strategic planning and policy formulation to facilitate smoother AI adoption in the industry.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

Based on these findings, it was concluded that senior management in Nairobi's commercial banks generally have a favorable perception of adopting artificial intelligence in investment decision-making processes. They recognize AI's potential to improve efficiency, accuracy, and competitiveness within the banking sector. The positive outlook is largely driven by strong leadership support, a culture that values innovation, and the availability of necessary technological resources and skilled personnel. However, concerns regarding security risks, data privacy, and potential job displacement serve as significant barriers that influence their perceptions negatively. Additionally, the level of organizational readiness and staff attitudes play crucial roles in shaping perceptions toward AI adoption. It was also concluded that successful integration of AI relies heavily on addressing these concerns through effective risk management, employee training, and ensuring organizational preparedness. Overall, while the outlook remains optimistic, the study emphasizes that overcoming perceived risks and fostering a supportive environment are essential steps toward fully harnessing AI's benefits in investment decision-making within the banking sector in Nairobi. This understanding can guide strategic planning and policy formulation to facilitate smoother AI adoption in the industry.

5.2 Recommendations

Based on the study's findings, it is recommended that commercial banks in Nairobi County prioritize strengthening their organizational readiness to facilitate AI adoption. This can be achieved by investing in staff training and capacity-building programs to enhance employees' understanding and skills related to AI technologies, thereby fostering a positive attitude towards innovation. Additionally, banks should establish comprehensive cybersecurity and data privacy measures to mitigate security risks and build trust among management and stakeholders. Leadership commitment is crucial; therefore, senior management should actively champion AI initiatives, promoting a culture of innovation and openness to technological change. It is also advisable to develop clear policies and frameworks that address ethical considerations and potential job displacement concerns, ensuring transparency and fairness in AI deployment. Furthermore, banks should explore partnerships with technology providers and academia to access cutting-

edge AI solutions and expertise, accelerating their digital transformation journey. Lastly, fostering an organizational environment that encourages experimentation and continuous improvement will help address perceived organizational readiness issues and enhance overall acceptance of AI technologies. Implementing these recommendations can help banks leverage AI's full potential while minimizing associated risks, ultimately leading to more effective and competitive investment decision-making processes.

Future studies could investigate the impact of AI on customer satisfaction and service delivery, as well as its influence on organizational performance and profitability. Longitudinal studies would be valuable to examine how perceptions and adoption patterns evolve over time as AI technologies mature and organizational experiences accumulate. Further research is needed to evaluate the long-term effects of AI integration on organizational culture and workforce dynamics within the banking industry.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp0630a>
- Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, 7, 3–11. <https://starlab-alliance.com/wp-content/uploads/2017/09/The-Business-of-Artificial-Intelligence.pdf>
- Familoni, B. T., & Shoetan, P. O. (2024). Cybersecurity in the financial sector: A comparative analysis of the USA and Nigeria. *Computer Science & IT Research Journal*, 5, 850–877. <https://doi.org/10.51594/csitrj.v5i4.1046>
- Field, A. P. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage.
- Gregory, J., & Sovacool, B. K. (2019). The financial risks and barriers to electricity infrastructure in Kenya, Tanzania, and Mozambique: A critical and systematic review of the academic literature. *Energy Policy*, 125, 145–153. <https://doi.org/10.1016/j.enpol.2018.10.026>
- Haidari, M. N. (2023). Impact of decision-making on investment performance: A comprehensive analysis. *Psychometric Journal*, 12(4), 980–990. <https://doi.org/10.62345/jads.2023.12.4.7>
- Han, Y., Chen, J., Dou, M., Wang, J., & Feng, K. (2023). The impact of artificial intelligence on the financial services industry. *Academic Journal of Management and Social Sciences*, 2(3), 83–85. <https://doi.org/10.54097/ajmss.v2i3.8741>
- Huang, A. H., & You, H. (2023). Artificial intelligence in financial decision-making. In *Handbook of artificial intelligence and financial decision-making* (Chap. 15). Edward Elgar Publishing. <https://www.elgaronline.com/edcollchap/book/9781802204179/book-part-9781802204179-29.xml>
- Königstorfer, F., & Thalmann, S. (2020). Applications of artificial intelligence in commercial banks – A research agenda for behavioral finance. *Journal of Behavioral and Experimental Finance*, 27, Article 100352. <https://doi.org/10.1016/j.jbef.2020.100352>
- Kowalkiewicz, M. (2024). *The economy of algorithms: AI and the rise of the digital minions*. Policy Press. <https://doi.org/10.2307/jj.10354686>
- Kumar, S., Gupta, U., Singh, A. K., & Singh, A. K. (2023). Artificial intelligence. *Journal of Computers, Mechanical and Management*, 2, 31–42. <https://doi.org/10.57159/gadl.jcmm.2.3.23064>
- Luan, S., Reb, J., & Gigerenzer, G. (2019). Ecological rationality: Fast-and-frugal heuristics for managerial decision making under uncertainty. *Academy of Management Journal*, 62(6), 1735–1759. <https://doi.org/10.5465/amj.2018.0172>
- March, J. G., & Simon, H. A. (1980). The theory of organizational equilibrium. In A. Etzioni & E. W. Lehman (Eds.), *A sociological reader on complex organizations* (pp. 16–21). Holt, Rinehart, and Winston.
- Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, A. (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research*, 93, 67–78. <https://doi.org/10.1016/j.jbusres.2018.08.029>
- Mishra, A. K., Anand, S., Debnath, N. C., Pokhariyal, P., & Patel, A. (2024). *Artificial intelligence for risk mitigation in the financial industry*. John Wiley & Sons.



- Remmers, C., Topolinski, S., Buxton, A., Dietrich, D. E., & Michalak, J. (2017). The beneficial and detrimental effects of major depression on intuitive decision-making. *Cognition and Emotion*, 31(4), 799–805. <https://doi.org/10.1080/02699931.2016.1154817>
- Shoetan, P. O., & Familoni, B. T. (2024). Transforming fintech fraud detection with advanced artificial intelligence algorithms. *Finance & Accounting Research Journal*, 6(4), Article 4. <https://doi.org/10.51594/farj.v6i4.1036>
- Simon, H. A. (1979). Rational decision making in business organizations. *American Economic Review*, 69(4), 493–512.
- Stewart, H., & Jürjens, J. (2017). Information security management and the human aspect in organizations. *Information & Computer Security*, 25(5), 494–534. <https://doi.org/10.1108/ICS-07-2016-0054>
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124–1131.
- Uzonwanne, F. C. (2016). Rational model of decision making. In A. Farazmand (Ed.), *Global encyclopedia of public administration, public policy, and governance*. Springer. https://doi.org/10.1007/978-3-319-31816-5_2474-1
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal studies. *Management Science*, 46, 186–205. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Yin, R. K. (2017). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.