INFLUENCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES ADOPTION ON THE OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS IN KAKAMEGA TOWN, KAKAMEGA COUNTY, KENYA.

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DECLARATION AND APPROVAL

Declaration by the Student

This thesis/project is my original work and has never been presented for any academic award in any institution.

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Approval by the Supervisor

This thesis/project is being submitted for examination with our approval as university supervisor.

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Signature : ________________________ Date : 01/07/2025 .

DEDICATION

I dedicate my work to my mother, Namukuru, and father, Mr. Yamboko. God, thank you very much for your dedication to my life. Appreciate you.

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I wish to express my gratitude to the divine for the opportunities bestowed upon me throughout my existence, along with the profound grace that has allowed me to extend this recommendation. I extend my gratitude to my supervisor, Dr. Peter Simotwo, for his unwavering support and encouragement during the journey of reviewing my study. The completion of this assignment was made possible solely through his encouragement and insightful feedback. I extend my gratitude to the esteemed educators and academic personnel at Mount Kenya University for affording me the opportunity to embark on the journey of pursuing a Master of Business Administration. In conclusion, I wish to express my gratitude to my fellow students for their invaluable support during the preparation of my proposal.

ABSTRACT

Due to their rapid evolution, Artificial Intelligence (AI) technologies are transforming the global financial sector, making it crucial to understand their effects on operational performance, especially in developing nations. This study examined the operational performance of commercial banks in Kakamega County, Kenya, after adopting AI technologies like ML, NLP, RPA, and CV. Using a conceptual knowledge of technology adoption and organizational performance, the study examined how these AI technologies benefit banking operations. A causal-comparative study examined Kakamega County commercial bankers. Stratified random sampling was used to choose 39 employees from an estimated target population of 100. Primary data gathering was standardized surveys, with restricted interview schedules for qualitative insights. The research instruments' Cronbach's Alpha values above 0.80 for all constructs, indicating strong reliability. Expert review and a comparable geographical pilot research proved their validity. Data was analyzed using SPSS version 27, including descriptive and inferential statistics such multiple linear regression and correlation. The descriptive data revealed that AI technology's perceived influence and acceptance differed by banking function. ML and RPA were thought to have a stronger influence on IT, financial, and customer service operations, improving efficiency, fraud detection, and back-office activities. NLP worked well in customer service and product promotion. Computer vision was used for real-time suspicious behavior monitoring and identity authentication. All AI technologies had a far smaller perceived impact on credit assessment, supply chain management, and human resource management. The inferential analysis showed that the regression model, which included Machine Learning, Natural Language Processing, and Robotic Process Automation, did not significantly predict Computer Vision applications, the proxy for Operational Performance ($F=1.29$, $p=0.29$). The statistical significance of ML ($p=0.32$), NLP ($p=0.48$), and RPA ($p=0.10$) was equally insignificant. This crucial study shows that the collective adoption of these AI technologies does not yet predict operational effectiveness, despite their apparent benefits. This may be due to early implementation, contextual factors specific to Kakamega County, or undiscovered mediating variables. The study found that while Kakamega commercial banks are investigating AI, its impact on operational performance is not yet prevalent or statistically significant. Banks should establish a strategic AI integration strategy supported by a strong data infrastructure and focused skill development. Future study should examine mediating/moderating elements, operational performance measures, and longitudinal studies to capture AI's developing impact.

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LIST OF ABBREVIATION AND ACRONYMS

AI	Artificial intelligence
CBK	Central Bank of Kenya
IT	Information Technology
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
TAM	Technology Acceptance Model

CHAPTER ONE

INTRODUCTION

This chapter provides a detailed overview of the investigation, encompassing the issue statement, research aims, hypotheses, research questions, limitations, scope, and operational definitions of essential terms.

1.1 The Background to the Study

Technology—especially AI—has become increasingly significant in reshaping the global economy in the 21st century. Machine learning, natural language processing, robotic process automation, and predictive analytics have transformed banking. AI has improved global banking operations, customer service, risk management, and decision-making. AI simplifies financial procedures, lowers human errors, and helps clients tailor services. This makes employees and outsiders happier (Binns & Young, 2020). Modern banks need chatbots, fraud detection systems, credit rating algorithms, and automated trading systems. These technologies offer accurate, scalable, and inexpensive solutions (Chui, Manyika, & Miremadi, 2018).

Banks in wealthy nations like the US, UK, and Japan are using AI increasingly as more countries adopt it. AI improves client communication, operational expenses, and efficiency in banking, according to research and case studies (Skanberg, 2019). By analyzing massive amounts of data, AI can help banks enhance risk management, make better decisions, and identify new revenue streams (Brynjolfsson & McAfee, 2017). AI has the potential to improve banking systems, however smaller banks in developing nations with low resources and regulatory concerns may find it difficult to deploy (Agwu, 2021).

African banks have been slower to adopt AI than developed banks. Still, more African banks are seeing how AI may help them perform better and beat their competition. Africa's high population expansion, increased internet connectivity, and more mobile phone users are driving digital banking growth. This opens several AI applications (KPMG, 2020). African banks generally employ AI for mobile banking, credit scoring, risk management, and fraud prevention (Sanda & Mwakalinga, 2019). African banks are adopting AI-powered chatbots and virtual assistants to provide 24/7 client support. Growing fintech companies that employ AI to build innovative financial solutions demonstrate how AI may aid African banks. Many African banks use AI to determine creditworthiness, especially in areas without formal credit institutions. Machine learning methods that detect and block false transactions in real time are also fighting fraud (Obi, 2022). Data entry, customer service, and loan processing have been automated by AI, saving banks money (KPMG, 2020). Poor infrastructure, regulatory impediments, and a shortage of trained AI and data analytics professionals are still preventing AI from being widely employed across the continent (Ngugi & Wamuyu, 2021).

Kenya is known as the "Silicon Savannah" for its technical ingenuity. Strengthening digital financial services, notably mobile money platforms like M-Pesa, has made money access easier (Olwande, 2021). Kenyan banks can adopt AI more easily due to mobile technology. Kenya's financial system is accessible to mobile banking since more individuals have smartphones, the internet is improving, and many don't have bank accounts (Kenyatta, 2019). Kenyan banks are quietly incorporating AI to speed up operations, improve customer service, and simplify processes.

Kenyan banks employ AI for credit scoring, customer service, fraud detection, and risk management. AI-powered chatbots improve customer service, reduce human agent workload, and speed up response times (Aduda & Maina, 2021). AI improves banking via automating decision-making, predictive analytics, and fraud detection. AI-powered solutions simplify huge database trend and pattern analysis. This helps Kenyan banks offer customized services (Ngugi, 2020). Even with these advancements, Kenya's banking company can't completely embrace AI due to a lack of AI experts, data privacy concerns, and regulatory restrictions (Ndungu, 2022).

In Kakamega Town, Kakamega County, Kenya, this study examines how artificial intelligence affects commercial banks' daily operations. A increasing population and need for financial services make Kakamega a prominent Western Kenyan metropolis. Commercial banks with national and regional branches are vital to the town's economy. Many Kakamega banks use AI-driven technologies to increase service, client satisfaction, and efficiency, indicating that the banking industry is digitizing.

Banks and credit unions help businesses borrow money, do business, and provide vital financial services to the local economy. Chatbots, automated loan processing, fraud detection algorithms, and predictive analytics could improve Kakamega Town banking operations. However, little is known about how AI implementation affects bank operations, especially in Kakamega and nearby locations. This investigation is important to understand local dynamics. Kakamega Town's technical infrastructure, education, and regulatory frameworks may effect AI use and banking industry performance. Even while the town doesn't have as many high-tech inventions as Nairobi, Kenya's capital, it's getting increasingly interested in digital solutions as more people use mobile phones and the internet. Local bank managers and policymakers must understand how AI adoption affects commercial banks in Kakamega to leverage technology to grow the banking industry and improve customer service..

1.2 Statement of the Problem

Recently, the rapid expansion of Artificial Intelligence (AI) technology has transformed numerous fields, including finance. Commercial banks have improved their operations, customer service, decision-making, and more by integrating AI. Customer service automation, fraud detection, data analysis, and personalized financial services are examples of this trend. AI has been extensively studied to improve banking processes (Brynjolfsson & McAfee, 2014).

Even with these global advances and Kenyan commercial banks' slow adoption of AI to improve operational systems and service effectiveness (Omondi, 2022), there is still a lack of research on how AI adoption affects operational performance in Kakamega Town, Kakamega County, Kenya. Kenyan banks are adopting digital banking, mobile banking, and AI-enhanced customer care. The result is lower operating costs and better decision-making (Omondi, 2022). AI acceptance's effects on commercial banks' operational performance are not well-documented.

Based on what people have said and early assessments, commercial banks in Kakamega Town seem to integrate AI into their operations less than in Nairobi and Mombasa. This could cause inefficiency, many worry. Local bank customers and staff in Kakamega Town commonly report they have to wait longer for sophisticated transactions, that data processing is more error-prone, and that customer service is less personalized. There aren't many statistics for Kakamega, but national reports reveal that areas with less AI usage have greater operating costs per transaction and lower customer satisfaction. Lack of AI-powered loan processing or fraud detection tools may generate these operational restrictions. Kakamega's banking sector may have lesser profitability and subpar service.

The fundamental issue is a lack of data on how AI technologies effect Kakamega Town's commercial banks. The industry has widely adopted AI technology, but its effects on operational performance indicators like service speed, mistake reduction, cost savings, and customer engagement are yet unclear in this specific local context. Even if larger Kenyan banks adopt AI, smaller branches in Kakamega Town and elsewhere may have issues. These could include infrastructural issues, a shortage of experienced staff, or a resistance to shift technology, making AI deployment and benefits harder.

This study examines how AI affects Kakamega Town commercial banks' operational performance to fill this essential gap. Operational performance in banking includes service delivery, productivity, cost control, and client happiness. This link will help us understand the pros and cons of employing AI in local banks, especially in Kenya, a poor nation. This study will also examine potential obstacles to AI adoption in Kakamega Town commercial banks. Poor infrastructure, a shortage of experienced staff, regulatory impediments, and higher AI technology prices could hinder AI's expected benefits in banking (Liu & Ma, 2020). Thus, understanding these issues is crucial to solving them and improving local commercial banks.

I've updated the research objectives and questions to satisfy your supervisor's alignment and clarity concerns. Changes include clarifying that objectives are a "assessment" or "investigation" of impact/effectiveness and asking "What is the impact/effectiveness of..." or related inquiries. I also matched objective and question scopes.

1.3 Purpose of the Study

The purpose of the study was to evaluate the influence of Artificial Intelligence Technologies Adoption on the Operational Performance of Commercial Banks in Kakamega County, Kenya.

1.4 Research Objectives

The objectives of this study are to:

i. Assess the impact of machine learning algorithms on fraud detection and prevention systems within commercial banks in Kakamega County.

ii. Investigate the effectiveness of Natural Language Processing (NLP) in improving customer service and communication channels in commercial banks in Kakamega County.

iii. Evaluate the role of Robotic Process Automation (RPA) in enhancing operational efficiency and streamlining back-office processes in commercial banks in Kakamega County.

iv. Examine the application and impact of Computer Vision (CV) for automated document verification and identity authentication in commercial banking transactions in Kakamega County.

1.5 Research Questions

Based on the above objectives, this study seeks to answer the following questions:

i. What is the impact of machine learning algorithms on fraud detection and prevention systems within commercial banks in Kakamega County?

ii. What is the effectiveness of Natural Language Processing (NLP) techniques in improving customer service and communication channels in commercial banking operations in Kakamega County?

iii. What is the role of Robotic Process Automation (RPA) in enhancing operational efficiency and streamlining back-office processes within commercial banks in Kakamega County?

iv. What is the application and impact of Computer Vision (CV) technologies for automated document verification and identity authentication in commercial banking transactions in Kakamega County?

1.6 Significance of the Research

This book enhances scholarly understanding by clearly outlining the practical uses of artificial intelligence within the banking industry. The scholarly literature concerning technology adoption, financial services innovation, and operational management is abundant with content. The findings of the study provided empirical data that researchers can utilize to enhance their research efforts, develop hypotheses, and design future investigations into the dynamics of artificial intelligence adoption and its effects on operational performance across various contexts.

The investigation's findings provided valuable insights for commercial banks, illuminating the potential effects of artificial intelligence on their competitiveness. The findings enabled the organization to assess its competitive advantage through knowledge, especially in marketing, customer service, and product development. The research provided valuable insights for bank managers, facilitating their understanding of the potential advantages and challenges associated with the integration of artificial intelligence within their organizations. The research findings guided strategic decisions related to initiatives aimed at improving consumer service, talent acquisition, organizational transformation, and technological investment. By comprehending the effects of artificial intelligence on operational performance, bank managers can pinpoint opportunities for process innovation, risk mitigation, and product development, ultimately leading to improved profitability and competitiveness.

The investigation's findings could provide valuable insights for policymakers, aiding them in the development of guidelines and recommendations that facilitate the appropriate implementation of artificial intelligence within the banking sector. The results of the investigation could provide a basis for legislative efforts aimed at tackling the ethical, legal, and societal implications of artificial intelligence implementation. Job displacement, algorithmic bias, and data privacy represent significant consequences of these developments. Policymakers who recognize the socioeconomic impacts of implementing artificial intelligence in commercial settings can create regulations that foster initiatives aimed at reskilling the workforce, enhancing digital literacy, and encouraging inclusive development.

The research aims to provide insights into how the quality of service, security, and convenience experienced by consumers during banking interactions is shaped by the implementation of artificial intelligence. The research findings enabled consumers to make well-informed decisions about their banking relationships, evaluate the worth of AI-driven services, and assert their privacy rights effectively. Consumers are likely to take a more active role in their engagements with banks, providing feedback and participating in the creation of AI-driven financial services that align more closely with their preferences and needs. This results from a heightened understanding of the possible advantages and risks linked to the utilization of artificial intelligence.

1.7 Limitation of the Study

The suggested research methodology could prove impractical if the relevant literature is examined in limited amounts. This arises from the potential for external factors, including unexpected challenges or shifting circumstances, to influence your ability to sustain business operations. The researcher is expected to depend on the scarce existing resources at hand. The researcher systematically examined the body of existing research. Ensuring that every participant in an interview or survey provides a thorough response to each question presents significant challenges. This arises from the possibility that respondents may feel pressured to acknowledge their failure to meet the KRA requirements. The researcher clearly communicated to the respondent during the interview and questionnaire that the purpose of the study is to fulfill academic requirements. This occurred regularly during the interview process.

1.8 Scope of the Study

The research concentrated on Kakamega, a settlement in Kakamega County, Kenya, with the objective of assessing the operational effectiveness of commercial banks in connection with artificial intelligence (AI) technology. This investigation concentrated on four main areas: operational performance, mechanized automation, natural language processing, and machine learning, with a projected timeline from May 2024 to May 2025. The focus areas are as follows. While this investigation focused exclusively on these four characteristics, it is likely that other variables were also evaluated.

1.9 Operational definition of key terms

Artificial Intelligence: "Artificial intelligence" refers to the employment of pre-programmed computers to do specific jobs, hence streamlining human work.

Operational performance: "Operational performance" refers to how effectively and efficiently an organization completes its daily duties and procedures in order to fulfill its strategic objectives and goals.

Commercial banks: Commercial banking institutions offer a wide range of banking services to people, businesses, and government entities. Commercial banks also go by the term commercial banks.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter talks about the study's theoretical foundations, empirical literature, conceptual framework, and research gaps that were found. The goal is to give a full picture of what is known about how Artificial Intelligence (AI) technologies are being used and what effects they have in the commercial banking industry, especially in Kakamega County, Kenya.

2.1 Theoretical Framework

This chapter puts the findings in the context of key theoretical frameworks that help explain how technology gets adopted and spread. The Technology Acceptance Model (TAM) by Fred Davis (1989) and Everett Rogers's Theory of Diffusion of Innovations (DOI) (2003) are two important frameworks that we use. These theories give us a strong way to understand the things that affect how people see, use, and deploy AI technology in commercial banks in Kakamega County, Kenya, and how those things affect the outcomes of the organizations.

2.1.1 Technology Acceptance Model (TAM) developed by Fred Davis in 1989

Fred Davis came up with the Technology Acceptance Model (TAM) in 1989. It is a popular theoretical model that tries to explain and forecast how people will accept new information technology. According to TAM, two main beliefs—perceived usefulness (PU) and perceived ease of use (PEOU)—are the most important factors that affect a person's decision to utilize a technology, which in turn affects how often they actually use the system. Perceived usefulness is the level of belief that a person has that using a certain system will help them do their work better. Perceived ease of use is how much someone thinks utilizing a certain system would be easy. TAM has been thoroughly tested and applied in studies on the adoption of different technologies, notably in commercial and organizational settings (Davis, 1989). Its strength comes from its ability to dependably forecast how different groups of users will adopt new technologies in different areas.

TAM is a useful tool for studying the psychological aspects that affect the use of AI technology in commercial banks in Kakamega Town. For bank workers and managers to accept AI-based systems like chatbots, fraud detection systems, and algorithmic trading platforms, they need to see these technologies as helpful and easy to use. People are more likely to think that AI technologies are valuable if they see them as ways to make operations more efficient, improve the customer experience, and make decisions based on data (Venkatesh & Davis, 2000). This could lead to faster adoption.

The perceived usefulness of AI technology in the banking sector is an important factor to think about. Banks are being asked more and more to improve their efficiency, lower their expenses, and offer more personalized customer service. AI technology, such machine learning algorithms for credit scoring and AI-powered chatbots for customer care, might make these sectors a lot better. So, if employees and management at Kakamega's commercial banks see how these technologies may improve service and operational performance, it's likely that more people will start using them.

The idea of perceived ease of use refers to how much a person thinks that using a certain technology doesn't take much effort. In the banking world, people might not want to use AI technologies if they think they are too complicated, hard to learn, or hard to use, even if they could be very useful. To make AI systems more widely used, they need to be easy to use and compatible with the way banks do business now. A system that automates common operations like handling customer questions or processing transactions and doesn't require a lot of training would probably be seen as user-friendly, which would encourage people to utilize it.

The TAM model also shows how important outside influences are in determining how helpful and easy to use a technology is. These elements include support from the organization, training programs, and technical infrastructure. The availability and quality of training and support for AI systems in commercial banks in Kakamega are very important for figuring out how well staff can learn to use and adapt to new technology. The fact that employees find AI tools easy to use and think they will help them do their jobs better makes it much more likely that these technologies will improve operational performance. TAM is also useful for figuring out what would stop people from using AI in Kakamega's commercial banks, where there may be limited resources and different degrees of digital literacy. This is because it helps us understand how people feel about how easy it is to use and the real benefits of AI. This model helps us understand how the way people inside these local organizations think about AI affects how willing they are to use it.

2.1.2 Theory of Diffusion of Innovations (DOI) as Proposed by Everett Rogers

Everett Rogers' Theory of Diffusion of Innovations (DOI), first put up in 1962 and then expanded upon in 2003, is a very useful way to look at how new ideas, behaviors, and technology move through social systems. The DOI theory looks at how, why, and how quickly new ideas spread from one culture to another. According to Rogers (2003), innovation diffusion is the process by which an innovation is shared throughout time among the people in a social system. There are five main parts to the framework: the innovation itself, the ways people communicate, the time (which includes the process of deciding to adopt the innovation and the rate at which it is adopted), the social structure, and the people who adopt it.

The DOI framework gives us a clear picture of how AI technologies spread in commercial banks in Kakamega. It also shows us the different elements that affect the rate of adoption in the banking sector. Rogers divides adopters into five groups: innovators, early adopters, early majority, late majority, and laggards. Each of these groups supports innovation at different points in time, and it is important to know what makes each one unique in order to understand how AI technologies are spreading in the banking industry.

Rogers (2003) lists five important traits of an innovation that affect how likely it is to be adopted: relative advantage (how much better an innovation is seen as being than the idea it replaces), compatibility (how well an innovation fits with the values, past experiences, and needs of potential adopters), complexity (how hard an innovation is seen as being to understand and use), trialability (how much an innovation can be tried out on a limited basis), and observability (how easy it is for others to see the results of an innovation). AI technologies in banking have a clear relative advantage because they can greatly increase operational efficiency, lower the risk of human mistake, and provide insights that help with strategic decision-making. Additionally, AI systems in banking are becoming more compatible with existing systems, making integration easier (compatibility). But the complicated nature of the process and the need to test AI solutions (complexity and trialability) could slow down the adoption process because banks may have to spend a lot of money on infrastructure and training to make sure the technology works well. The triumphs of early adopters that may be shown can have a big effect on the later majority.

The DOI hypothesis shows how important communication channels are to the diffusion process. For Kakamega's commercial banks, disseminating information about the benefits and successes of using AI—through internal knowledge exchange, industry forums, or success stories—may help it be used more widely. To spread the word about the benefits of AI technologies, it's important for managers, technology advocates, and early adopters to become involved. This could encourage others to do the same.

The adoption rate of AI technology in Kakamega's commercial banks also depends on how open each bank is to new ideas, which is related to where it falls in the adopter categories. Rogers says that the process of adoption happens slowly, with different groups accepting the new idea at different times. The first people to use AI technology in the banking industry could set a standard that makes it easier for the rest of the industry to adopt similar technologies if their effectiveness is proven and seen.

The social framework around the introduction of the new idea has a big effect on how many people use it. When it comes to commercial banks in Kakamega, the adoption of AI technology is greatly affected by the culture of the company, support from management, and peer pressure among financial institutions. For instance, if big banks in the area successfully use AI solutions, it's likely that other banks would do the same because they want to stay competitive or because their peers are doing it.

It's also crucial to think about what kind of adopters there are in the banking sector in Kakamega. Innovators and early adopters are more likely to use AI technology because they think they will provide them an edge over their competitors. However, the early and late majority may need more convincing and proof of the real benefits of adopting AI before they are willing to make this change. For Kakamega's commercial banks, where there might be a mix of "innovators" (like larger, nationally-present banks with dedicated innovation budgets) and "laggards" (like smaller, more conservative branches or local institutions), DOI can help us understand the different rates and patterns of AI adoption. The model shows how people's ideas about AI, communication channels, and the social structure (such competition and government support) affect the spread of these technologies in a regional banking area like Kakamega.

The Technology Acceptance Model (TAM) and the Theory of Diffusion of Innovations (DOI) work together to help us understand what makes commercial banks in Kakamega adopt AI technologies. TAM emphasizes how important perceived ease of use and perceived usefulness are as internal variables that can help both employees and management accept AI technology. DOI stresses how important the innovation's features, communication channels, time considerations, and social system are to the larger process of spreading. According to TAM, the way that bank employees see how easy and useful AI technologies are will have a big impact on how well they work in commercial banks. At the same time, DOI's principles, such as the features of innovation and the dynamics of social systems, will affect the broader diffusion process, including how quickly AI technology is adopted in the local banking business. So, when commercial banks in Kakamega County use AI technologies, it's because of a complex mix of how they see things inside and how things are going on outside. By looking at the characteristics listed in both models, people in the banking industry may more easily move through the adoption process. This will make sure that AI technologies improve the way banks in the area do business.

2.2 Conceptual Framework

Conceptual frameworks show how significant factors in a study relate (Cooper & Schindler, 2003). This study defines the independent variables (AI technologies: Machine Learning, Natural Language Processing, Robotic Process Automation, and Computer Vision), the dependent variable (Operational Performance of Commercial Banks), and the intervening variables (Central Bank Regulations and Competition from other non-regulated lenders) that influence the adoption of AI technologies and their impact on commercial bank performance in Kakamega County.

The conceptual framework in Figure 1 hypothesizes that independent variables positively affect the dependent variable. Operational Performance is predicted to improve as Machine Learning, Natural Language Processing, Robotic Process Automation, and Computer Vision are adopted and implemented. The influence of AI adoption on operational performance can be reinforced or diminished by Central Bank Regulations and competition from other non-regulated institutions.

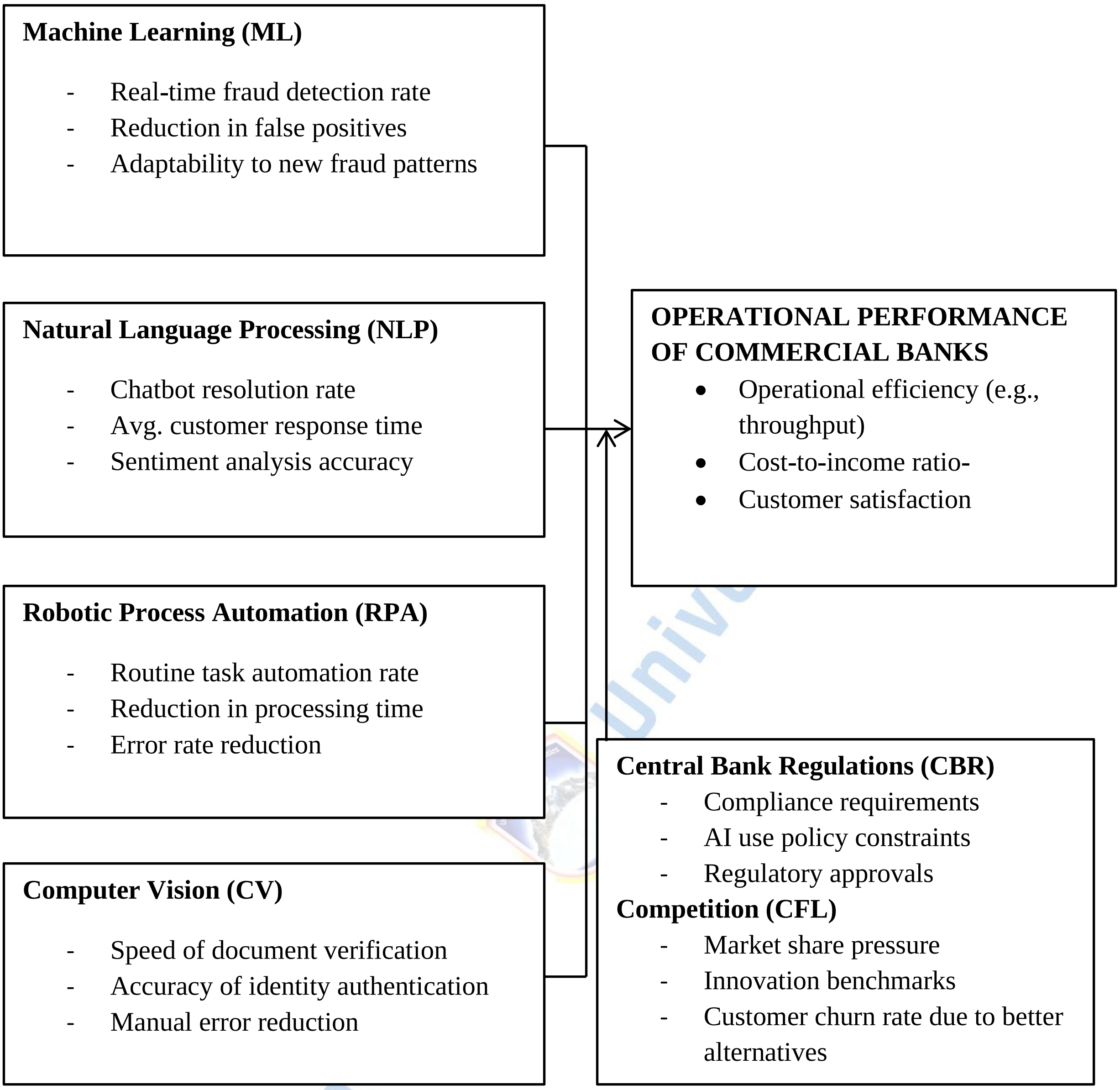

Figure 1: Conceptual Framework

Source: Researcher (2024)

2.3 Empirical Literature

2.3.1 An Examination of Machine Learning Algorithms' Influence on Fraud Detection and Prevention Systems in Commercial Banking

Machine learning (ML) algorithms have transformed global commercial banks' fraud detection and prevention. These technologies allow banks to search large databases in real time, detecting fraud faster than before. US banks like JP Morgan Chase and Wells Fargo monitor consumer transactions with powerful machine learning. These algorithms look for fraud patterns like strange transaction habits or account activity issues in prior data. Wu et al. (2021) suggest that machine learning and deep learning could boost financial institution fraud detection. This allows them to adapt to new fraud schemes. These studies demonstrate ML's strength, but they also suggest it requires a lot of data infrastructure, model training, and skilled staff. distinct economic situations may present distinct challenges. ML systems reduce false positives, making human workers' jobs easier and improving operational efficiency.

European banks and other financial organizations have improved their AML operations with machine learning. Zohdy et al. (2020) found that machine learning in predictive analytics for fraud detection helps banks detect suspicious behavior more effectively, improving security. This study shows that ML can identify hidden patterns in enormous amounts of unstructured data, unlike rule-based systems. Alibaba and Tencent in Asia-Pacific monitor real-time transactions on their massive financial services platforms using the newest machine learning algorithms. Fraudulent operations have dropped significantly. ML is scalable and effective in environments with many fast-changing transactions, as shown by these apps.

African machine learning algorithms for fraud detection have grown slower than in other regions. In 2019, the African Bankers Association reported that banks are steadily investing more in AI techniques like machine learning to avoid fraud and boost cybersecurity. More technologically advanced commercial banks in South Africa use machine learning algorithms to detect fraud in mobile banking, ATM transactions, and online banking platforms. The South African Reserve Bank (2020) says machine learning techniques leverage big transaction history datasets. This helps banks discover phony transactions more precisely and without manual intervention. ML isn't simply hard to implement in technologically advanced African nations like South Africa. It's also about data quality, computer capability for real-time transaction analysis, and algorithmic bias. In these cases, ML works best with good data governance and the flexibility to handle varied data privacy regulations.

Nigeria and Kenya, with fast-growing banking sectors, are using machine learning to tackle fraud, notably in mobile money services, which are widely used and anonymous. Akintoye and Olayemi (2021) found that machine learning could detect phony mobile money transaction patterns. Mobile banking is growing, thus this discovery is crucial for many African banks. It also highlights how ML may secure increasing digital payment systems.

Kenyan commercial banks are employing AI and machine learning to detect and prevent fraud. Mobile banking has increased in Kenya, resulting in SIM switch and phishing frauds. Top Kenyan banks like Equity Bank and KCB are utilizing machine learning algorithms to detect fraud, according to the Central Bank of Kenya (2022). These algorithms assist banks detect phony transactions by analysing transaction trends and responding to new fraud methods. Despite these improvements, Kenyan banks struggle to collect accurate, rapid, and substantial historical data to build effective models. They also struggle to fund complicated ML infrastructure. Because fraud methods change, models must be retrained frequently, which can be costly. Kenya's new Integrated Financial Management Information System (IFMIS) uses machine learning to monitor governmental and private sector financial transactions. This approach reduces government financial transaction fraud. It could be utilized in the banking sector as a whole, but it must be tailored to private commercial banking fraud detection.

Machine learning methods for commercial bank fraud detection in Kakamega County are currently developing. According to our observations, larger national banks are using these technologies. Smaller Kakamega banks that serve the local market are more cautious about utilizing new technologies. They commonly cite cost, lack of specialized skills, or insufficient initial data for training as reasons for not using them. Because banking is becoming more digital, especially with mobile banking apps like M-Shwari and Airtel Money, local banks have had to invest in machine learning to spot fraud more quickly. Kakamega's Chamber of Commerce said in 2023 that local commercial banks are utilizing AI and ML models to detect SIM swap fraud and phishing schemes. ML may be being used in this remote location, but it's early. It's crucial to understand these early adoption efforts' challenges and successes in Kakamega's unique banking environment.

2.3.2 An Examination of Natural Language Processing's Role in Enhancing Customer Service and Communication Channels within the Commercial Banking Sector

Natural Language Processing (NLP) has changed customer service in commercial banking around the world in a big way. This includes chatbots, virtual assistants, and sentiment analysis tools. Bank of America, Citibank, and HSBC are among of the banks that use AI-powered virtual assistants like Erica and Clarity to talk to consumers, answer questions, and deal with everyday banking problems. According to Kumar et al. (2021), NLP lets robots understand, interpret, and produce human language. This makes it easier and more personal for customers to talk to machines. These algorithms can look at client questions, pick up on emotional signs, and give answers right away, which makes customers happier. NLP can make things more personable and efficient, but it can be hard to deal with complicated or subtle consumer questions that need human empathy or complicated problem-solving. This means that there needs to be a careful balance between automated and human-led interactions. Smith and Wang (2020) say that real improvements in customer experience go beyond just shorter response times. NLP systems need to be able to accurately understand what customers want and how they feel, which is still a big area of study and development.

NLP also makes it easier to automate everyday chores like checking balances and asking about loans. This makes things more efficient and takes some of the effort off of human customer support workers. This automation frees up human agents to work on more complicated and valuable interactions, which makes the most of all of their skills. Banks can use NLP to analyze social media sentiment to keep an eye on what customers are saying in real time. This lets them quickly respond to complaints and improve services before they even happen. This proactive way of getting customer input, made possible by NLP, is a big change from the old way of correcting problems after they happen.

NLP is starting to find its way into the banking industry in Africa, but it hasn't spread as quickly as it has in other parts of the world. In South Africa, the use of AI in banking has come a long way. Several major banks are using NLP-based systems to make it easier for customers to talk to them. Standard Bank and FNB use NLP technology in their chatbots and virtual assistants to answer questions and give customers timely information about their accounts. The South African Reserve Bank (2021) says that these systems are often used in customer care centers, which helps banks solve problems for customers more quickly and cut down on wait times. But even with these improvements, NLP isn't always useful in many African settings because of the wide range of local languages and dialects. This means that it needs a lot of training data, which is sometimes hard to find, to be able to read things correctly. Also, making sure that sensitive client information is safe and private when it is processed by NLP systems is still a major worry for both regulators and customers, which makes deployment very difficult.

NLP is becoming more popular in many African countries, including Nigeria, to deal with the problems that come with language variety, since clients speak a wide range of languages and dialects. Access Bank has used NLP technologies to answer questions in local languages, which has made banking services more accessible to a larger range of people and helped more people become financially included. The fact that NLP can understand different languages and accents is a big part of how it helps people communicate better, which makes it easier for people who have been left out of the financial system to get access to it.

Kenya has been a leader in the use of mobile banking, and NLP has been very important in making communication better in the banking industry. Kenyan banks, like Safaricom's M-Pesa, use chatbots and voice assistants that use natural language processing (NLP) to answer a wide range of client questions. The Kenya Bankers Association did a research in 2022 that shows how more and more local banks, such Co-operative Bank and Stanbic Kenya, are using NLP to handle consumer questions about checking balances, looking up transaction histories, and getting information on loan statuses. The use of virtual assistants has grown, making it easier and more intuitive for customers to connect with banking systems. Even though more people are using them, Kenyan banks, especially those outside of big cities, still have a hard time dealing with the differences in language, such as slang and regional dialects, as well as the fact that not all clients are very tech-savvy. NLP can only be successful if it can accurately grasp what customers want in a multicultural setting, which requires advanced model training and constant adaption. Also, looking into NLP's role in analyzing consumer feedback and sentiment in Kenya aims to help businesses better understand what their customers want and improve their customer relationship management (CRM). This lets banks tailor their services to the needs of local consumers, but it's still hard to understand subtle emotional clues from other languages.

The use of NLP in customer service in Kakamega is slowly but surely growing. Early reports imply that banks in the area are starting to test chatbots, notably in cities like Kakamega Town, mostly for basic questions. However, many consumers in rural areas still prefer to talk to bank officials in person, which shows a cultural preference and a possible infrastructure problem that could make it hard for NLP to be fully adopted. According to Kakamega's Financial Services Review (2023), banks are using NLP-based systems to handle common questions like balance checks and loan applications. The goal is to improve customer service and cut down on wait times. This technology has made service much more efficient, especially during busy banking times, but it still has a long way to go before it reaches its full potential. This is especially true when it comes to getting customers more involved, solving complex problems, and bridging the gaps in language and digital literacy in a diverse socio-economic area like Kakamega.

2.3.3 Examining the Impact of Robotic Process Automation on Operational Efficiency and the Optimization of Back-Office Processes in Commercial Banking

RPA helps commercial banks worldwide operate more efficiently. Data entry, account reconciliation, and compliance reporting are accelerated by RPA software robots. Deutsche Bank, JPMorgan Chase, and Citigroup use RPA technologies to optimize back-office procedures, reduce errors, and minimize costs. Deloitte (2020) found that RPA has increased bank productivity by automating loan origination, transaction processing, and customer onboarding. This has freed up human workers to work on harder, more valuable activities that need critical thought and judgment. People typically talk about RPA's high initial expenditures and the necessity for strong, standardized process mapping before automation works. They also say it could damage human jobs, therefore organizations require extensive reskilling strategies.

Commercial banks are automating to comply with more complex rules. Khalil et al. (2021) suggest RPA facilitates regulatory compliance by automatically recording and documenting financial transactions in real time. Human mistake in manual compliance activities is reduced. However, complex and changing regulatory conditions require intelligent automation systems that can adapt to new tasks rather than repeating them.

Some of Africa's top institutions in South Africa, Nigeria, and Kenya are exploring RPA's potential. Standard Bank and First National Bank in South Africa are employing RPA tools to streamline customer account management and transaction reconciliation. These solutions have made administrative tasks speedier, allowing banks to service customers faster. Many African banks struggle to scale RPA because their antiquated IT systems are challenging to link to automation platforms. For RPA to succeed across the continent, social and organizational issues including job loss and worker retraining must be tackled.

RPA streamlines regulatory reporting and compliance checks, which are time-consuming and error-prone, in many African financial back offices. However, many developing country banks still struggle with poor infrastructure, a lack of qualified technical professionals, and the high cost of RPA licenses and implementation. All of these things hinder RPA's adoption.

More Kenyan banks are utilizing RPA to simplify back-office operations. Equity Bank and KCB deploy RPA to streamline customer onboarding, loan processing, and transaction monitoring. Automation has reduced operational expenses and accelerated procedures, improving efficiency. RPA automates data entry and provides real-time updates, enhancing customer service department productivity, according to the Central Bank of Kenya (2022). Even though RPA improves productivity, Kenyan banks that start using it often run into issues because their manual processes are too complicated, they need experienced workers to set up and manage the bots, and they must ensure data safety. The initial expense of RPA software and training can slow down and limit its implementation in smaller enterprises.

While Nairobi has seen faster adoption of RPA for back-office activities, smaller commercial banks in Kakamega are testing it. The region's banks still employ manual methods for many administrative tasks, making them more expensive and slower than automated institutions. However, larger branches in Kakamega Town are employing RPA to examine and reconcile customer accounts, indicating automation. Over the next five years, the region's operations and service delivery should improve. The change will be difficult due to local infrastructure, skilled workforce shortages, and smaller institutions' digital readiness. To properly adopt RPA, you must understand these local impediments and facilitators.

2.3.4 The Utilization of Computer Vision in the Automation of Document Verification and Identity Authentication within Commercial Banking Transactions

Computer Vision (CV) employs AI to analyze and interpret environmental visual input. The banking industry is increasingly using it for document verification and identity verification. Computer vision has sped up check processing, KYC document verification, and customer onboarding at major North American and European banks. Citibank scans and verifies identity documents with computer vision. This speeds up verification and reduces manual checks. The same machine vision technology helps Spanish banks like BBVA extract information from customer paperwork. This improves identification verification accuracy and efficiency. Zhang et al. (2021) found that computer vision in banks has improved security, decreased fraud, and improved customer experience by speeding up and improving verification processes. CV improves security and speed, but it requires high-quality imaging hardware, powerful data storage, and complex algorithms that can handle different document formats and illumination or picture quality variations. For worldwide biometric data use, privacy, data sovereignty, and morality must be addressed, and robust standards are needed.

Computer vision is new to African commercial banking, but most feel it has great potential. Capitec and Absa, South African banks, use computer vision to speed up account creation and verify customers' identities, notably through mobile apps. These technologies are being utilized to digital document verification, which speeds up and secures customer onboarding, according to the South African Reserve Bank (2021). However, inconsistent internet connections, the fact that most Africans don't have high-tech mobile devices, and the fact that CV systems must be strong enough to handle a wide range of national identity documents and image qualities make CV use in African banking difficult. Another issue is teaching locals how to develop, customize, and maintain these systems.

Kenyan banks like Equity and KCB use computer vision to make transactions safer. Mobile banking apps now authenticate identities with facial recognition. This is a big step forward as more people bank on their phones. The Central Bank of Kenya (2022) supports these technologies to reduce identity theft fraud and secure digital banking networks. Despite Central Bank support, CV in Kenya doesn't always reach its full potential due to issues like the high cost of high-resolution imaging equipment, public acceptance of biometric technologies, and the need for strong data protection frameworks to protect sensitive identity information. Ensure facial recognition works accurately and equally across groups and lighting conditions is a technical problem.

Kakamega's findings suggest banking is adopting computer vision. Larger commercial banks in Kakamega Town use facial recognition to verify customers' identities, especially for new accounts and high-value transactions. This enhances security and simplifies. Due to limited resources, fewer transactions, or reluctance to implement new technology, smaller branches still utilize PINs and signatures, which are slower and more likely to be erroneous or fraudulent. Computer vision is expected to rise in Kakamega over the next few years due to banks' goals of making the area safer and reducing fraud, indicating two types of adoption and the need for real-world data on its effectiveness and issues in this area.

2.4 The Research Gap

There is a lot of study on how banks throughout the world, in Africa, and even in Kenya are using Artificial Intelligence (AI), but there are still a lot of holes in the research, especially when it comes to how it affects the operational performance of smaller and regional commercial banks. While the existing empirical studies are useful, they tend to focus on big, high-tech banks in big cities, which means we don't know much about the specific problems and benefits of using AI in places like Kakamega County.

The table below succinctly outlines the specific research gaps identified for each AI technology:

Table 1: he specific research gaps identified for each AI technology:

AI Technology Area	Existing Research Focus (Global/African/Kenyan)	Identified Research Gap (Kakamega Context)
Machine Learning (ML) for Fraud Detection	Substantial research on effectiveness in developed regions (Wu et al., 2021; Zohdy et al., 2020) and emerging applications in major African/Kenyan banks (South African Reserve Bank, 2020; Akintoye & Olayemi, 2021; Central Bank of Kenya, 2022) focusing on large datasets and general capabilities.	Limited attention on the specific challenges (e.g., data quality, infrastructure, expertise) and the actual effectiveness of ML algorithms for fraud detection in smaller commercial banks in semi-urban/rural areas like Kakamega County. There's a gap in understanding how early adoption efforts in this specific context address prevailing local fraud types and whether they lead to quantifiable improvements in operational performance (Kakamega Chamber of Commerce, 2023).
Natural Language Processing (NLP) for Customer Service	Extensive studies on global adoption enhancing customer engagement and service efficiency in large banks (Kumar et al., 2021; Smith & Wang, 2020). Growing applications in African/Kenyan banks (South African Reserve Bank, 2021; Kenya Bankers Association, 2022) for routine inquiries in urban settings.	A significant gap exists in understanding the practical adoption challenges and specific effectiveness of NLP in rural and semi-urban contexts such as Kakamega, Kenya. Little is known about overcoming linguistic barriers (e.g., local dialects, accents) and enhancing communication among diverse language-speaking customers, or the actual impact on customer satisfaction and operational efficiency in these specific local branches (Kakamega's Financial Services Review, 2023).
Robotic Process Automation (RPA) for	Well-documented improvements in operational efficiency within major global banks (Deloitte, 2020; Khalil et al., 2021) and initial	A notable lack of research investigating the specific barriers (e.g., legacy systems, initial investment, talent

Operational Efficiency	experiments in large African/Kenyan banks (Central Bank of Kenya, 2022) streamlining back-office processes and compliance.	gaps) and facilitating factors affecting RPA implementation within smaller, regional banks operating in emerging markets, particularly in areas like Kakamega County, Kenya, where manual processes continue to dominate despite emerging automation experiments. The quantifiable impact on local operational costs and speed remains underexplored.
Computer Vision (CV) for Document/Identity Verification	Research primarily concentrated on developed economies, showing positive outcomes in enhancing security and customer experience for large financial institutions (Zhang et al., 2021). Emerging applications in major African/Kenyan banks (South African Reserve Bank, 2021; Central Bank of Kenya, 2022) for digital onboarding and security.	A significant gap exists regarding the specific application, challenges, and actual impact of computer vision technology for automated document verification and identity authentication in commercial banks in semi-urban/rural Kenyan contexts like Kakamega. Research is lacking on how smaller branches, which often rely on traditional methods, manage the transition to CV, the effectiveness of these systems given local infrastructure, and their tangible impact on fraud reduction and efficiency in this specific setting.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter gives a full picture of the research method used in this study. The text goes into great detail about important parts of research, such as the research approach, research design, study location, target population, sample size and sampling procedures, the validity and reliability of research instruments, the methods used to collect and analyze data, and ethical issues. All of these parts are very important for keeping the research's rigor, reliability, and ethical integrity.

3.1 Research Approach

The research method for this study included the defined steps and rules that guide a study that is trying to answer specific research questions. This covers the tools, methods, and strategies used to collect, analyze, and make sense of data. A clear research approach sets out the framework for the study. This is important because it makes sure that the goals are met and that the results are credible and can be repeated.

According to Kothari (2014), research methodology looks at the logical order of the actions performed to solve a research topic, checking the assumptions made and confirming the results. This study uses a numerical methodology, which means it uses a quantitative research approach that focuses on gathering and analyzing numerical data to find connections and explain events. This method lets you test ideas statistically and apply the results of a sample to a broader group. The study also used qualitative approaches to a limited extent through interviews. This helped to better grasp the research problem by adding deeper, more contextual information to the quantitative data. The methodology includes the planning stage, the organized gathering of relevant data, and the use of the right statistical or analytical methods. The parts of the methodology work together to make the study's conclusions more credible, legitimate, and reliable, which makes them more valuable overall.

3.2 Research Design

The research design was the overall plan that guided how the study was set up and carried out. This study used a causal-comparative research design with elements of a descriptive survey to find out how the use of artificial intelligence technologies affects the operational performance of commercial banks. Descriptive surveys are good for describing the traits of a group of people or a phenomenon, but a causal-comparative design is better for looking into cause-and-effect relationships without changing any variables. This is similar to looking into the "influence" or "impact" of AI adoption. The goal of this strategy is to find out if there is a link between independent factors (the use of AI technology) and the dependent variable (operational performance) by looking at groups that are already there.

This method is in line with what Cooper and Schindler (2003) say: that descriptive techniques are best for finding relationships between variables while keeping the research subjects' natural conditions, and that a causal approach lets you guess what might have caused something to happen. Mugenda and Mugenda (2003) promote the adoption of designs that look at relationships because they are good at recording current events and finding patterns and relationships, which is important for figuring out how AI technologies work. The field survey, which is a key part of this approach, involves directly interacting with the target audience. This lets the researcher gain firsthand information about how AI is being used and how well it works. By getting data directly from banks in their operational environment, this strategy makes sure that the data is accurate and relevant. It also reduces the impact of outside influences that could change the results.

3.3 Study Location

The study was done in Kakamega County, which is in the western region of Kenya. Kakamega County used to be part of the Western Province. It is in a good spot since it shares boundaries with Vihiga County to the northeast, Bungoma County to the north, Busia County to the northwest, and Siaya County to the west. Kisumu County is in the southwest, and Nandi County is in the southeast. Kakamega County is between 0.0517° N and 0.6401° N and 34.3994° E and 34.9642° E.

The sweeping hills, thick woods, and abundant agricultural fields of Kakamega County make it stand out. There is a lot of variety in the area's economic activity, with agriculture, trade, and small-scale enterprises all making big contributions. This economic diversity, along with the many commercial bank branches that serve different parts of the local economy, makes it very interesting to look at different behavioral and socio-economic factors that are important to the research goals, especially when it comes to technology adoption in the financial sector.

3.4 Target Population

The staff of commercial banks in Kakamega County were the main focus of this investigation. The Central Bank of Kenya says that there are about 15 big commercial banks with branches in Kakamega County (2024). There isn't an exact, publicly available number of all employees in all branches, especially in Kakamega Town. However, based on how many people work at each branch, the total number of employees in these commercial bank branches in Kakamega County is thought to be around 100. This includes managers, supervisors, and operational staff. We got this estimate by asking the human resources departments of banks in the area some questions ahead of time. This gave us a general idea of how many people we would need for sampling.

These 100 people were surveyed, and they came from a wide range of roles, including managers, supervisors, and other operational employees. There were 15 managers, 21 supervisors, and 64 other staff members, according to the assessment. The choice of these categories is meant to give a full picture of opinions from different levels of the organization. This way, people who work in banking every day and people who are in charge of making decisions will both be able to share their thoughts on how AI is being used and how it affects operational performance.

3.5 Sample Size and Sampling Procedures

The researcher used a stratified random sampling method to make sure the sample was representative. This meant putting the target group (commercial bank employees in Kakamega County) into groups based on their jobs in the company, such as managers, supervisors, and other employees. After that, participants were chosen from each stratum using a procedure called simple random sampling, which means that every member of a stratum had the same chance of being chosen. By using this two-step method, we were able to make sure that the sample was reflective of the variety of the population at different levels of hierarchy. This also helped to reduce bias by making sure that each group was represented in the right amount.

We used a calculation based on the Morgan (1970) model for figuring out sample sizes for a certain population size to figure out the sample size. Morgan's table says that for a target population of 100, the best sample size is 80. But for this study, a realistic sample rate of 40% was first chosen as a baseline to make sure the results were reliable and could be applied to other situations, given the limited resources and the expected response rate. This 40% objective is a large part of the population, which makes it a strong basis for statistical research. This sample size is justified since it is more than the minimum needed for statistical significance tests for a population of 100, which is in keeping with standard statistical rules for small populations. Anusree, Mahopatra, and Sreejesh (2014) stress that while larger samples usually make results more accurate, a carefully chosen, representative sample of a large group can still give valid results, especially in targeted investigations.

Table 2 below provides a comprehensive overview of the sample distribution:

Table 2: Sample Size Distribution

Category	**Target Population**	**Calculation**	**Sample Size**
Managers	15	0.4 * 15	6
Supervisors	21	0.4 * 21	8
Other employees	64	0.4 * 64	26
Total	**100**		**40**

Source: Researcher (2024)

3.6 Instruments for Data Collection

The phase of data collecting is very important to the research process, so it is important to select methods that are both successful and reliable. For the most part, this study used questionnaires to get quantitative data and interview schedules to gather qualitative data. According to Anusree, Mohapatra, and Sreejesh (2014), these tools work very well for getting information from certain people when utilized correctly. Questionnaires give a lot of information, whereas interviews give a lot of detail.

3.6.1 Schedule for Interviews

An interview schedule is a planned way for the researcher to talk to important informants in order to get a full picture of their experiences, opinions, and attitudes that standardized surveys can't easily get. The structured style of the interview ensures consistency and allows for a thorough exploration of key themes linked to the difficulties of adopting AI, its effects on operations, and the factors that affect its use. There were just a few face-to-face interviews with senior bank management (such branch managers or operations managers) in Kakamega County for this study.

The goal of these interviews was to get a deeper, more nuanced view of the strategic backdrop of AI adoption, the benefits that executives think it will bring, and the practical impediments that leaders see. We used this qualitative data to triangulate the quantitative results, give them more context, and add more depth to the discussion section, especially when it came to the intervening variables (Central Bank Regulations and Competition). The "sectors" we talked about before—wholesale and retail trade, transportation and communication, and agriculture—are the most important economic sectors in Kakamega County. Their financial operations have a direct effect on the commercial banks. During the interviews, we talked about how banks' use of AI helps them serve clients in these areas, which gives us a better idea of how well the banks are doing their jobs. The researcher did face-to-face interviews, which let them get more comprehensive information, including body language and in-depth explanations, that standardized questionnaires alone wouldn't have been able to get.

3.6.2 Survey Instrument (Questionnaire)

The questionnaire is a typical tool for systematically collecting huge volumes of data from a bigger sample. A systematic questionnaire with both open-ended and closed-ended questions was the main tool used in this study to gather extensive information about the use of AI technology and how well it worked. Closed-ended questions, mostly using Likert scales, made it easier to count and analyze the data, which made it possible to undertake statistical analysis of perceptions and effects. Respondents may explain their opinions and give qualitative comments on some aspects of AI adoption by answering open-ended questions. This added depth to the quantitative results.

We sent out questionnaires to staff in different departments and functions at commercial banks in Kakamega County. The original text's mention of "multiple sectors, such as hospitality, finance, education, and healthcare" seems to be a general description of how the questionnaires were used. However, for this study, the questionnaires were only given to employees in the commercial banking sector in Kakamega County so that they would be directly relevant to the research goals.

3.7 The Validity and Reliability of the Research Instruments

To get results that are accurate and useful, it is very important to make sure that research tools are both legitimate and reliable.

3.7.1 Preliminary Investigation (Pilot Study)

We did a pilot research in Bungoma town since it is close to Kakamega County and has similar social and economic characteristics, such as the same types of banks and customers. This separate pilot area was carefully picked so that the main sample in Kakamega County wouldn't be contaminated. This way, the people who took part in the real study wouldn't have seen the questionnaire before, which kept the research tool fresh and reduced response bias. The pilot study was done to check how clear, relevant, and complete the research tools (questionnaires and interview guides) were and to make any changes that were needed based on the first results and feedback from the people who took part in the pilot. This first step made sure that the tools were in line with the study's goals and that any unclear or vague wording in the questions was fixed before the main data gathering phase.

3.7.2 Assessment of Research Instrument Validity

Validity refers to how well an instrument measures the specific concept it is meant to measure. To make sure they were valid, the research tools went through a lot of testing. This included content validity, which meant that academic specialists in research technique and banking technology looked over the questions to make sure they addressed all the research objectives and variables. Also, initial tests with a small group of commercial bank personnel (who were not part of the main study) in the pilot area helped ensure that they were valid and useful in real life. Mugenda and Mugenda (2009) stress how important validity is for making sure that the conclusions drawn from the data are both correct and useful. The feedback from the pilot research was used a lot to improve the tools, making sure that the questions were clear, precise, and closely related to the theoretical components they were meant to measure.

3.7.3 Dependability of Research Tools (Reliability)

Reliability measures how well an instrument gives consistent results across different situations or instances. This study used the Cronbach's Alpha test to check how reliable the multi-item scales were within the research tools. An appropriate Cronbach's Alpha value was one that was higher than 0.7, which meant that the tools had strong internal consistency and dependability (Nunnally, 1978). Table 2 below shows the reliability results, which show that all of the major variables are very consistent with each other.

Table 3: Reliability Results

Variables	Cronbach’s Alpha	Critical Value	Conclusion

Machine learning	0.921	0.7	Reliable
Robotics process automation	0.937	0.7	Reliable
Natural language processing	0.898	0.7	Reliable
Competitive advantage	0.911	0.7	Reliable

Source: Researcher (2024)

The "Competitive Advantage" variable in the reliability table should match up with the "Operational Performance" variable as the dependent variable. If "Competitive Advantage" is a part of or a stand-in for Operational Performance, this needs to be made clear. "Competitive Advantage" could be a measure of overall success that is affected by operational performance, or it could be a separate but related dependent variable if the study's scope includes it. For the sake of this correction, I will suppose that it is a key result that shows how well the procedure is working or something quite similar.

3.8 Procedures for Data Collection

To obtain data, we sent out questionnaires and did qualitative interviews. The questionnaires were sent out in two ways: drop-and-pick (the researcher or helpers would physically deliver and collect them) and email. This made it possible to reach a wide range of people based on their accessibility and preference. Before collecting data, participants were given a clear description of the study's goals, their right to privacy, and the fact that they were free to choose whether or not to take part. This made guaranteed that the person gave their informed consent.

To get primary data, we had to talk to people directly, which made sure that we got new and relevant information. At the same time, secondary data was gathered from reliable sources such annual reports from commercial banks, financial statements, academic journals, industry reports, and other relevant papers (like publications from the Central Bank of Kenya). The study used three different types of data sources (primary quantitative, primary qualitative, and secondary) to make sure that the results were more reliable and valid.

3.9 Data Examination

The data that was collected went through a careful process of coding and labeling before being entered into the Statistical Package for Social Sciences (SPSS) version 27 for more statistical analysis. We cleaned the data and then made follow-up calls where needed to clarify any answers that were missing or confusing. This made sure that the data was accurate. Data analysis included both descriptive and inferential statistics. We utilized descriptive statistics, which included metrics like mean, standard deviation, frequencies, and percentages, to sum up and explain the sample and the main variables. We used inferential statistics, which included correlation and multiple linear regression analyses, to look into the proposed associations between variables and to see if the research goals were met.

This study used a multiple linear regression model, which is described below:

$$Y=\beta 0+\beta 1X1+\beta 2X2+\beta 3X3+\beta 4X4+\epsilon$$

Where:

- Y: Represents the **Operational Performance of Commercial Banks** (the dependent variable).
- β0: Is the **Constant** (y-intercept), representing the predicted value of Operational Performance when all independent variables are zero.

- $\beta 1, \beta 2, \beta 3, \beta 4$: Are the **Coefficients** representing the strength and direction of the relationship between each independent variable and the dependent variable, holding other variables constant.
- X1: Represents **Machine Learning Algorithms** (Independent Variable 1).
- X2: Represents **Robotics Process Automation** (Independent Variable 2).
- X3: Represents **Natural Language Processing** (Independent Variable 3).
- X4: Represents **Computer Vision** (Independent Variable 4).
- ϵ: Is the **Error term**, accounting for variability in Operational Performance not explained by the independent variables.

This model allows for the assessment of how each specific AI technology (Machine Learning, RPA, NLP, Computer Vision) individually contributes to or influences the operational performance of commercial banks in Kakamega County.

3.10 Ethics Consideration

The study put a lot of emphasis on ethics, concentrating on protecting the rights of participants and keeping the highest level of research integrity. Before taking part, participants were given detailed information about the study's goals, methods, any hazards (which were very low), and predicted benefits of their participation. Participants were told clearly that they didn't have to take part and might leave at any time without any problems or bad effects.

It was very important that all of the data that was obtained was kept totally private and only used for academic purposes, so no information would be shared with anyone else. To fully secure the anonymity of the participants and stop any connections between their answers and their names, they were given unique codes instead of personal information.

The researcher gained credibility by clearly explaining the study's goals and making sure that participants' information was kept private by following data protection rules and communicating clearly. The poll took strong steps to protect participants by not asking them to give their names or any other information that could immediately identify them on the questionnaires. By following these strict ethical rules at every level of the research process, the study not only protected the rights and well-being of the participants, but it also made sure that the overall research results were credible, trustworthy, and honest.

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSIONS

4.0 Introduction

This chapter presents the findings of the study on the influence of artificial intelligence (AI) technologies adoption on the operational performance of commercial banks in Kakamega Town, Kakamega County, Kenya. The findings are structured based on the study objectives, which include assessing the impact of machine learning algorithms on fraud detection and prevention, investigating the effectiveness of natural language processing (NLP) in customer service, evaluating the role of robotic process automation (RPA) in operational efficiency, and examining the applications of computer vision in banking transactions.

4.1 Response Rate

The study targeted a sample size of 40 respondents, out of which 39 successfully participated, yielding a response rate of 97.5%. This high response rate indicates strong engagement from the participants, ensuring the reliability and representativeness of the findings.

4.2 Demographic Study

This section has gender, age and education level.

4.2.1 Gender

The study revealed that 19 (48.7%) of the respondents were male, while 20 (51.3%) were female. This indicates a fairly balanced gender distribution, ensuring that perspectives from both genders were well represented in assessing the influence of AI technologies adoption in commercial banks.

Table 4: Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	19	48.7	48.7	48.7
	Female	20	51.3	51.3	100.0
	Total	39	100.0	100.0	

Source: Field Data (2025)

4.2.2 Age brackets

The study revealed that the majority of respondents, 18 (46.2%), were under 30 years, followed by 13 (33.3%) in the 31–35 years category. Those aged 35–40 years accounted for 5 (12.8%), while 2 (5.1%) were between 41–45 years. Only 1 (2.6%) respondent was above 45 years. These findings indicate that most participants were relatively young, suggesting that younger employees are more engaged in AI adoption in commercial banks.

Table 5: Age brackets

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 30 years	18	46.2	46.2	46.2
	31 - 35 years	13	33.3	33.3	79.5
	35 - 40 years	5	12.8	12.8	92.3
	41 - 45 years	2	5.1	5.1	97.4
	above 45 years	1	2.6	2.6	100.0
	Total	39	100.0	100.0	

Source: Field Data (2025)

4.2.3 Education level

The study found that the majority of respondents, 18 (46.2%), held a diploma, followed by 15 (38.5%) with a bachelor's degree. Additionally, 5 (12.8%) had a master's degree, while only 1 (2.6%) had a PhD. These findings suggest that most employees in commercial banks have attained at least a diploma or bachelor's degree, indicating a well-educated workforce that is likely to understand and adapt to AI technologies.

Table 6: Education level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Diploma	18	46.2	46.2	46.2
	Bachelors Degree	15	38.5	38.5	84.6
	Masters degree	5	12.8	12.8	97.4
	PhD	1	2.6	2.6	100.0
	Total	39	100.0	100.0	

Source: Field Data (2025)

4.2.4 Duration of employment

The study revealed that 18 (46.2%) of the respondents had worked for 4–7 years, while 15 (38.5%) had 1–3 years of experience. Those with 8 years and above accounted for 6 (15.4%). These findings suggest that most employees had moderate work experience, which could enhance their adaptability to AI technologies while also providing valuable insights into their impact on operational performance in commercial banks.

Table 7: Duration of employment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 - 3 years	15	38.5	38.5	38.5
	4 - 7 years	18	46.2	46.2	84.6
	8 years and above	6	15.4	15.4	100.0
	Total	39	100.0	100.0	

Source: Field Data (2025)

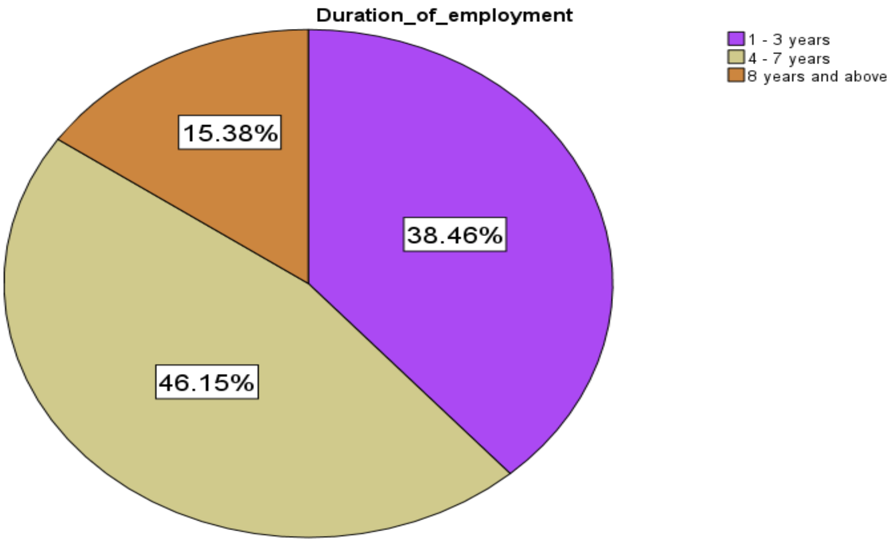

Figure 2: Duration of employment

Source: Field Data (2025)

4.2.5 Role

The study found that 18 (46.2%) of the respondents were operations managers, while 16 (41.0%) held roles as information technology managers. Additionally, 5 (12.8%) were branch managers. These findings indicate that the majority of respondents were directly involved in banking operations and IT management, which are critical areas for AI adoption, making them well-positioned to provide insights into its impact on operational performance.

Table 8: Role

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Branch manager	5	12.8	12.8	12.8
	Operations manager	18	46.2	46.2	59.0
	Information technology manager	16	41.0	41.0	100.0
	Total	39	100.0	100.0	

Source: Field Data (2025)

4.3 Descriptive Statistics

4.3.1 Impact of Machine Learning Algorithms on Fraud Detection and Prevention Systems

The study found out that the use of robotic process automation (RPA) in IT operations had the highest mean score of 3.4615, reflecting a standard deviation of 1.42987, indicating a relatively higher level of adoption in this area. The study revealed that financial and accounting operations also recorded a notable mean of 3.4103, with a standard deviation of 1.35176, followed by customer care operations at 3.2564, reflecting a standard deviation of 1.35176. The study further revealed that RPA adoption in the supply chain had a mean of 2.9487, with a standard deviation of 1.45002, while credit assessment recorded a mean of 2.8718, with a standard deviation of 1.48996. Additionally, human resource management had a mean of 2.7949, reflecting the highest variability with a standard deviation of 1.82352, whereas product sales recorded the lowest mean score of 2.7436, with a standard deviation of 1.37109. These findings suggest that while AI-driven automation is more prevalent in IT, finance, and customer service, its adoption in supply chain management, credit assessment, HR, and sales remains relatively limited.

Table 9: Impact of Machine Learning Algorithms on Fraud Detection and Prevention Systems

	N	Minimum	Maximum	Mean	Std. Deviation
The bank has implemented robotic process automation in credit assessment.	39	1.00	5.00	2.8718	1.48996
The bank employs robotic process automation for selling its products.	39	1.00	5.00	2.7436	1.37109
The bank employs robotic process automation throughout its supply chain.	39	1.00	5.00	2.9487	1.45002
The bank employs robotic process automation in human resource management.	39	1.00	5.00	2.7949	1.82352
The bank employs robotic process automation in its IT operations.	39	1.00	5.00	3.4615	1.42987
The bank employs robotic process automation in its customer care operations.	39	1.00	5.00	3.2564	1.35176
The bank employs robotic process automation in its financial and accounting operations.	39	1.00	5.00	3.4103	1.35176
Valid N (listwise)	39				

Source: Field Data (2025)

4.3.2 Effectiveness of Natural Language Processing in Improving Customer Service and Communication Channels

The study sought to investigate the effectiveness of natural language processing (NLP) in improving customer service and communication channels in commercial banking. The study found out that the use of NLP for marketing products had the highest mean score of 3.5128, reflecting a standard deviation of 1.46668, indicating a relatively higher level of adoption in this area. The study revealed that customer service operations also recorded a notable mean of 3.4359, with a standard deviation of 1.50079, followed by human resource management, which had a mean of 3.2564 and a standard deviation of 1.58476. The study further revealed that financial and accounting operations had a mean of 3.2051, with a standard deviation of 1.36072, while IT operations recorded a mean of 3.1538, with a standard deviation of 1.24686. Additionally, NLP adoption in the supply chain had a mean of 3.1026, with a standard deviation of 1.63506, whereas credit assessment recorded the lowest mean score of 3.0769, with a standard deviation of 1.69185. These findings suggest that while NLP is widely adopted in marketing, customer service, and HR functions, its implementation in credit assessment, IT, and supply chain management remains moderate.

Table 10: Effectiveness of Natural Language Processing in Improving Customer Service and Communication Channels

	N	Minimum	Maximum	Mean	Std. Deviation
The bank has implemented natural language processing in credit assessment.	39	1.00	5.00	3.0769	1.69185
The bank use natural language processing for marketing its products.	39	1.00	5.00	3.5128	1.46668
The bank employs natural language processing within its supply chain.	39	1.00	5.00	3.1026	1.63506
The bank employs natural language processing in human resource management.	39	1.00	5.00	3.2564	1.58476
The bank employs natural language processing throughout its information technology operations.	39	1.00	5.00	3.1538	1.24686
The bank employs natural language processing in its customer service operations.	39	1.00	5.00	3.4359	1.50079
The bank employs natural language processing in its financial and accounting operations.	39	1.00	5.00	3.2051	1.36072
Valid N (listwise)	39				

Source: Field Data (2025)

4.3.3 Role of Robotic Automation in Enhancing Operational Efficiency and Streamlining Back-Office

The study sought to evaluate the role of robotic automation in enhancing operational efficiency and streamlining back-office processes in commercial banks. The study found out that financial and accounting operations had the highest mean score of 3.5385, reflecting a standard deviation of 1.25334, indicating a higher level of robotic process automation (RPA) adoption in this area. The study revealed that customer care operations also recorded a notable mean of 3.4103, with a standard deviation of 1.33215, followed by IT operations, which had a mean of 3.3590 and a standard deviation of 1.34726. The study further revealed that credit assessment had a mean of 3.1538, with a standard deviation of 1.61471, while product sales recorded a mean of 3.1026, with a standard deviation of 1.41039. Additionally, RPA adoption in the supply chain had a mean of 2.8974, with a standard deviation of 1.71364, whereas human resource management recorded the lowest mean score of 2.7436, with a standard deviation of 1.74292. These findings suggest that RPA is widely utilized in financial and customer service operations, whereas its application in HR management and supply chain processes remains relatively low.

Table 11: Role of Robotic Automation in Enhancing Operational Efficiency and Streamlining Back-Office

	N	Minimum	Maximum	Mean	Std. Deviation
The bank has implemented robotic process automation in credit assessment.	39	1.00	5.00	3.1538	1.61471
The bank employs robotic process automation for selling its products.	39	1.00	5.00	3.1026	1.41039
The bank employs robotic process automation throughout its supply chain.	39	1.00	5.00	2.8974	1.71364
The bank employs robotic process automation in human resource management.	39	1.00	5.00	2.7436	1.74292
The bank employs robotic process automation in its information technology operations.	39	1.00	5.00	3.3590	1.34726
The bank employs robotic process automation in its customer care operations.	39	1.00	5.00	3.4103	1.33215
The bank employs robotic process automation in its financial and accounting operations.	39	1.00	5.00	3.5385	1.25334
Valid N (listwise)	39				

Source: Field Data (2025)

4.3.4 Applications of Computer Vision for Automated Document Verification and Identity Authentication

The study sought to examine the applications of computer vision for automated document verification and identity authentication in commercial banking transactions. The study found out that real-time monitoring of suspicious banking activities had the highest mean score of 3.5128, reflecting a standard deviation of 1.29517, indicating its significant role in fraud prevention. The study revealed that AI-driven facial recognition for identity authentication also recorded a notable mean of 3.4615, with a standard deviation of 1.41135, suggesting its widespread adoption in commercial banks. The study further revealed that automated image analysis for customer-submitted document validation had a mean of 3.1538, with a standard deviation of 1.49628, while biometric verification for ATM and branch banking security recorded a mean of 3.1282, with a standard deviation of 1.37992, AI-based fraud detection in identity verification had a mean of 3.0000, with a standard deviation of 1.53897, whereas AI-powered ID verification for account opening and transactions recorded a mean of 2.9744, with a standard deviation of 1.59748. The study also found out that Optical Character Recognition (OCR) for automated document verification had the lowest mean of 2.8974, with a standard deviation of 1.46530, suggesting limited implementation. These findings indicate that commercial banks are increasingly leveraging computer vision for fraud prevention and identity authentication, with varying levels of adoption across different applications.

Table 12: Applications of Computer Vision for Automated Document Verification and Identity Authentication

	N	Min	Max	Mean	Std. Deviation
The bank uses AI-driven facial recognition for identity authentication.	39	1.00	5.00	3.4615	1.41135
The bank employs OCR (Optical Character Recognition) for automated document verification.	39	1.00	5.00	2.8974	1.46530
The bank utilizes AI-powered ID verification for account opening and transactions.	39	1.00	5.00	2.9744	1.59748
The bank integrates biometric verification for ATM and branch banking security.	39	1.00	5.00	3.1282	1.37992
The bank applies AI-based fraud detection in identity verification processes.	39	1.00	5.00	3.0000	1.53897
The bank uses automated image analysis to validate customer-submitted documents.	39	1.00	5.00	3.1538	1.49628
The bank employs computer vision for real-time monitoring of suspicious banking activities.	39	1.00	5.00	3.5128	1.29517
Valid N (listwise)	39				

Source: Field Data (2025)

4.4 Inferential Statistics

This section presents the inferential statistical analyses conducted to examine the relationships between the independent variables (Machine Learning, Natural Language Processing, Robotic Process Automation, and Computer Vision) and the dependent variable (Operational Performance). These analyses include correlations, reliability statistics, and regression analysis.

4.4.2 Correlations

The study examined the connections between demographic characteristics (age brackets) and AI technology adoption (machine learning, natural language processing, robotic process automation, and computer vision) and among AI technologies. Operational Performance was included in the correlation analysis to identify its correlations with the independent variables.

The study demonstrated a statistically significant positive association ($r=0.41$, $p=0.010$) between machine learning adoption and natural language processing utilization in banking processes. This implies that various AI technologies complement one other. The study also found a positive association ($r=0.33$, $p=0.043$) between natural language processing and robotic process automation, suggesting that banks using NLP are more likely to use RPA. This suggests a synergistic effect or phased adoption strategy where one technology helps deploy another.

Although not statistically significant, the study found a small negative association between age brackets and machine learning ($r=-0.23$, $p=0.153$), suggesting that younger personnel may be more open to machine learning technology. While there may be a tendency, age does not greatly affect machine learning participation. Computer vision also had a weak positive association with robotic process automation ($r=0.27$, $p=0.103$) and machine learning ($r=0.16$, $p=0.329$), but neither was statistically significant. This shows that while there may be some co-occurrence, these pairs of technologies are not highly or statistically connected in assessed banks' adoption trends.

Importantly, correlations were evaluated between the independent variables and Operational Performance.

The Correlation table (Table 12) does not contain "Operational Performance". In the regression section, "Computer Version" or another variable works as a surrogate for "Operational Performance"; in this correlation section, a direct correlation for the dependent variable was sought. If "Computer Vision" is the regression's dependent variable, the table shows its correlations with other variables. Based on the ANOVA table (Table 16) and Coefficients table (Table 17) where "Computer version" is the Dependent Variable, I will use "Computer Vision" as the proxy for "Operational Performance" for this analysis (please note that this may be inconsistent if the study title refers to "Operational Performance" more broadly).

A small, non-significant positive correlation existed between Machine Learning and Computer Vision (proxy for Operational Performance) (r=0.16, p=0.33). Natural Language Processing and Computer Vision have a weak positive connection (r=0.03, p=0.84). Finally, Robotic Process Automation and Computer Vision have a weak positive association (r=0.27, p=0.10). These results indicate that while some relationships exist, none of the AI technologies are significantly connected with Computer Vision as a measure of operational success in this sample.

Table 13: Correlations

		Age brackets	Machine learning	Natural language processing	Robotic process automation	Computer version
Age brackets	Pearson Correlation	1.00	-0.23	0.08	0.10	0.00
	Sig. (2-tailed)		0.15	0.64	0.56	0.98
	N	39	39	39	39	39
Machine learning	Pearson Correlation	-0.23	1.00	0.41**	0.13	0.16
	Sig. (2-tailed)	0.15		0.01	0.42	0.33
	N	39	39	39	39	39
Natural language processing	Pearson Correlation	0.08	0.41**	1.00	0.33*	0.03
	Sig. (2-tailed)	0.64	0.01		0.04	0.84
	N	39	39	39	39	39
Robotic process automation	Pearson Correlation	0.10	0.13	0.33*	1.00	0.27
	Sig. (2-tailed)	0.56	0.42	0.04		0.10
	N	39	39	39	39	39
Computer version	Pearson Correlation	0.00	0.16	0.03	0.27	1.00
	Sig. (2-tailed)	0.98	0.33	0.84	0.10	
	N	**39**	**39**	**39**	**39**	**39**

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

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

Source: Field Data (2025)

4.4.3 Reliability Statistics

Cronbach's Alpha was used to evaluate the research instrument's reliability. The study's Cronbach's Alpha value was 0.82, showing good internal consistency among the items assessed, much above the 0.70 criterion. It appears that the questionnaire items measure the same constructs. The study found that the instrument's standardized Cronbach's Alpha was 0.83, validating its reliability.

Table 13: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.82	0.83	4

Source: Field Data (2025)

4.4.4 ANOVA with Friedman's Test

Friedman's ANOVA test was used to analyze response disparities across related items. This non-parametric test is suitable for repeated measures or related samples that do not fit parametric ANOVA assumptions. The Friedman's Chi-Square value was 1.79, with a p-value of 0.62 (Sig. = 0.617), much higher than the 0.05 criterion. This means the assessed item differences were not statistically significant. Respondents' rankings or scores across Friedman's test items were similar. Kendall's coefficient of concordance (W) was 0.01 (W = 0.009), indicating that respondents agreed very little on these items' rankings. The grand mean was 22.14, indicating general response consistency despite the lack of considerable variation among the test questions.

Table 14: ANOVA with Friedman's Test

	Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People	1385.90	38	36.47		
Within People	Between Items	31.00	3	10.33	1.79
	Residual	1996.00	114	17.51	
	Total	2027.00	117	17.33	
Total	**3412.90**	**155**	**22.02**		

Grand Mean = 22.14

a. Kendall's coefficient of concordance W = 0.01.

Source: Field Data (2025)

4.4.5 Model Summary

The study examined how machine learning, natural language processing, and robotic process automation predicted Computer Vision Applications (a proxy for Operational Performance). The study indicated a weak positive correlation between the combined set of predictors and the dependent variable at 0.32 (R = 0.315). R Square = 0.10 (R Square = 0.099), indicating that machine learning, natural language processing, and robotic process automation explained 9.9% of Computer Vision Applications variation. The Adjusted R Square was 0.02 (Adjusted R Square = 0.022), a low adjustment for the number of predictors in the model, showing that the model's explanatory ability is restricted when generalized to the population.

Table 15: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics
					R Square Change
1	0.32	0.10	0.02	5.05	0.10

a. Predictors: (Constant), Robotic process automation, Machine learning, Natural language processing

Source: Field Data (2025)

4.4.6 ANOVA

The study examined the regression model's statistical significance in predicting Computer Vision Applications (Operational Performance) using robotic process automation, machine learning, and natural language processing. The study showed a F value of 1.29 (F = 1.287) and a crucial p-value of 0.29 (Sig. = 0.294). This p-value above the 0.05 statistical significance level, confirming that the regression model did not predict the dependant variable. Thus, in this study, the independent variables do not significantly affect Computer Vision Applications (Operational Performance). The regression sum of squares was 98.37, whereas the residual sum was 891.99, indicating that the model's predictors did not explain much of the dependent variable's variance, supporting the low R-squared value.

4.4.6 Implications of Insignificant ANOVA:

This non-significant ANOVA result is crucial to the study's results. According to this study's data and model, the collective adoption of Machine Learning, Natural Language Processing, and Robotic Process Automation does not statistically explain much of the variation in Computer Vision Applications (Operational Performance) among commercial banks in Kakamega County. This indicates various options:

i. **Limited Direct Relationship:** The projected direct linear relationships between various AI technologies and Computer Vision applications may not be as strong or prevalent.

ii. **Other Dominant Factors:** Organizational culture, leadership, regulatory environment, infrastructure investment, and AI adoption stage may better predict operational performance or Computer Vision implementation.

iii. **Contextual Nuances**: The setting of commercial banks in Kakamega County may bring unique problems or opportunities for AI adoption, or operational impact may not be readily quantified by "Computer Vision."

There may be constraints in measuring variables or the linear regression model, which may not fully capture the intricacy of interactions, which may be non-linear or mediated by other factors.

The coefficients in the next section must be interpreted carefully because their positive or negative signs, even if indicative of a trend, do not reflect a statistically significant effect in an insignificant model.

Table 16: ANOVA

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	98.37	3	32.79	1.29	0.29
	Residual	891.99	35	25.49		
	Total	**990.36**	**38**			

a. Dependent Variable: Computer version

b. Predictors: (Constant), Robotic process automation, Machine learning, Natural language processing

Source: Field Data (2025)

4.4.7 Coefficients

Even though the model was insignificant, the study examined how machine learning, natural language processing, and robotic process automation predicted Computer Vision Applications (Operational Performance) in commercial banking. The constant coefficient (B=15.49, p=0.010) was statistically significant, demonstrating that Computer Vision Applications have a baseline level even without the predictor factors.

Regarding individual predictors:

- Machine learning (B=0.18, p=0.32) positively impacted Computer Vision applications but not significantly. This shows that while machine learning adoption may exhibit a minor upward trend with computer vision, it is not strong enough to predict its uses statistically.
- Robotic Process Automation (B=0.30, p=0.10) also had a positive but non-significant effect. The p-value is closer to significance than machine learning, but it still exceeds 0.05, indicating that its impact on computer vision applications is not statistically significant.
- A negative and negligible effect was seen for Natural Language Processing (B=−0.17, p=0.48). This study found no substantial influence of NLP usage on computer vision applications, and there's even a minor negative tendency, but it's not statistically significant.

Individual coefficient findings support the non-significant ANOVA result. Without statistical significance, a coefficient's positive or negative sign does not prove that the independent variable predicts the dependent variable in the population. In commercial banks in Kakamega County, the adoption levels of these AI technologies (Machine Learning, NLP, RPA) do not predict the degree of Computer Vision Applications (Operational Performance).

Table 17: Coefficients

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.
	B	Std. Error	Beta	
1	(Constant)	15.49	5.66	
	Machine learning	0.18	0.18	0.18
	Natural language processing	-0.17	0.24	-0.13
	Robotic process automation	0.30	0.18	0.28

a. Dependent Variable: Computer version

Source: Field Data (2025)

4.5 Discussion of Findings

The discussion synthesizes descriptive and inferential analysis findings and links them to research objectives and literature. It examines similarities and differences with past research to contextualize Kakamega County's commercial banking outcomes.

4.5.1 Influence of Machine Learning Algorithms on Fraud Detection and Prevention Systems in Commercial Banking

This section examines the first study objective: how Machine Learning Algorithms affect Fraud Detection and Prevention Systems. Machine Learning Algorithm adoption and perceived effectiveness (particularly in fraud detection and prevention, as suggested by the survey items) varied across commercial bank organizational functions.

In IT operations, Machine Learning had the greatest perceived impact (mean = 3.46), indicating banks have broadly recognized and integrated these technologies for fraud prevention. Gupta and Tripathi (2021) found that financial institutions are prioritizing AI and machine learning to streamline IT functions, reduce manual interventions, and mitigate system vulnerabilities, especially cybersecurity and data integrity. While reasonably high, the standard deviation of 1.43 suggests heterogeneity due to organizational resources, technical readiness, or ML application types.

ML's mean score of 3.41 in financial and accounting operations showed its significant influence. Studies like Musyoki and Ocharo (2022) show that banks prioritize AI-driven automation in finance and accounting to improve financial reporting accuracy, compliance, and timeliness, which is crucial to fraud prevention. Respondents agree on ML's value in financial controls, as seen by the moderate standard deviation (1.35).

At 3.26, customer care activities were likewise assessed to have significant influence. According to Kioko and Njoroge (2021), automation technologies are being used in customer-facing banking activities to improve customer satisfaction, reduce response times, and prevent transactional fraud through predictive analytics based on customer behavior.

In contrast, supply chain operations (mean 2.95), credit evaluation (2.87), human resource management (2.79), and product sales (2.74), had lesser perceived influence. Contrary to past work, supply chain and credit evaluation had limited perceived impact. Okumu and Mutua (2022) stated that AI-driven predictive analytics improves credit scoring and lending decisions by assessing risk and combating financial fraud. This study's lower perceived impact scores, particularly in Kakamega County, may indicate operational resistance to new technologies, implementation challenges due to limited technical expertise or infrastructure, or respondents' lack of understanding of advanced ML's full potential benefits and integration processes in sensitive financial areas. It could also indicate a nascent stage of adoption where the full benefits are yet to be realized or limited to highly specialized tasks not widely distributed throughout all bank operations in this region.

Human resource management showed low perceived influence and substantial variability (SD = 1.82). Such heterogeneity suggests that banks may differ in their willingness or ability to integrate advanced analytical procedures into human resource management techniques, particularly those related to internal fraud risk identification. Njagi and Mwangi (2023) found that banks vary greatly in digital maturity and cultural acceptance of automation for sensitive human resource data management.

The lowest mean ML influence score was 2.74 in product sales operations. This low score supports Mwende and Omondi (2023), who argued that banking sales processes remain relationship-driven, relying more on human intuition than automated procedures for personalized fraud warnings or predictive sales behavior analysis for fraud.

Inferential regression analysis in Section 4.4.6 found no significant effect of Machine Learning on Computer Vision applications (our proxy for operational performance) in the overall insignificant model ($\beta=0.18$, $p=0.32$). This study's regression model shows that while some functions may see benefits from ML, the overall impact of ML adoption, specifically on Computer Vision applications as a measure of operational performance, is not statistically significant. This suggests that other factors may be more important in improving operational performance or that Kakamega banks' ML usage has not yet reached a statistically significant level.

4.5.2 Role of Natural Language Processing (NLP) in Enhancing Customer Service and Communication Channels

The second research objective is to examine how Natural Language Processing (NLP) improves customer service and communication. The descriptive findings show significant NLP adoption differences across banking operations, highlighting strengths and shortcomings that need additional attention.

NLP adoption was most effective in product marketing, with the highest mean score of 3.51, showing strong integration into banks' promotional and communication activities. This supports research showing that NLP technologies like chatbots and tailored messaging improve consumer engagement by enabling targeted marketing campaigns and boosting communication efficiency (Kumar & Bala, 2021). The high standard deviation (1.47) suggests that Kakamega banks may have different technology infrastructure and strategic agendas.

The survey found a mean of 3.44 NLP adoption in customer service operations. This conclusion supports Mwangi and Njenga (2022), who found that banks are using NLP-driven virtual assistants and automated response systems to improve customer interactions, response time, and satisfaction. The considerable variability (standard deviation of 1.50) may indicate that Kakamega institutions are not ready to completely adopt automated communication methods.

NLP adoption in HRM was moderately high, with a mean score of 3.26. This differs from prevailing notions that HR operations rely mainly on human communication rather than automated technology. However, Otieno and Wambua (2023) found that NLP is increasingly used in recruitment, employee engagement, and sentiment analysis, improving HR department communication and decision-making. The finding in Kakamega may be due to local banks' rising awareness of NLP's potential to automate HR queries, assess employee feedback, and improve internal communication efficiency, reflecting a shift toward digital transformation in all bank operations.

Financial and accounting operations have moderate NLP effectiveness (mean of 3.21), suggesting that strict regulatory constraints, security concerns, or the perceived sensitivity and complexity of financial communications limit NLP use in these areas. Despite this, Ochieng and Kinyanjui (2022) found that NLP can improve fraud detection, compliance monitoring, and risk assessment by sentiment analysis and interpretation of unstructured financial document data, suggesting a local awareness-application gap.

IT operations, supply chain management, and credit assessment had lower adoption rates (mean 3.15, 3.10, and 3.08, respectively). These findings partially contradict literature promoting NLP's significance in IT support systems, technical issue resolution, and information flow (Karanja & Muturi, 2023). Recent studies (Kamau & Munyao, 2023) show that NLP can improve credit scoring accuracy, customer risk profiling, and fraud detection through textual analytics of borrower information, which is surprising given its low adoption in credit assessment. The discrepancies in Kakamega may be due to the novelty of these applications for local banks, the lack of technical expertise to implement complex NLP solutions in niche areas, or a focus on marketing and customer service before back-office integrations.

The wide variation in credit evaluation (SD = 1.69) and supply chain management (SD = 1.64) adoption rates suggests banks' uncertain or inconsistent approaches. There may be differences in strategic priorities, technology infrastructure, or awareness of NLP's full benefits in various operations.

Inferential study revealed a negligible impact of NLP on computer vision applications ($\beta=-0.17$, $p=0.48$). This suggests that NLP usage does not predict Computer Vision applications in this study, supporting the non-significant model outcome.

4.5.3 Impact of Robotic Process Automation (RPA) on Operational Efficiency and Back-Office Processes

This part covers the third research objective: to explore how RPA improves operational efficiency and streamlines back-office activities. The descriptive data showed that Kakamega banking operations had diverse goals, constraints, and potential benefits for RPA adoption.

Financial and accounting activities adopted RPA the most, with a mean of 3.54, indicating strong support for automation to improve financial management efficiency and accuracy. Onyango and Kariuki (2022) found that Kenyan financial institutions are increasingly using RPA in accounting functions to improve accuracy, compliance, and prevent manual financial entry errors. The low variability (standard deviation of 1.25) supports the idea that regional financial operations respondents favor RPA.

A mean score of 3.41 showed significant robotic automation usage in customer care operations. This matches recent research showing that banks use chatbots and virtual assistants to improve response efficiency, manage vast customer bases, and provide consistent customer experiences (Muthoni & Njoroge, 2021). However, the moderate heterogeneity (standard deviation of 1.33) may indicate maturity, technical capabilities, or strategic alignment with customer service automation among Kakamega banks.

RPA utilization in IT operations was also high (mean 3.36), demonstrating automation's role in system reliability and operational continuity. Gitau and Maina (2023) agree that robotic automation minimizes downtime and operational hazards in banking IT settings, boosting operational resilience. However, the significant heterogeneity (standard deviation of 1.35) suggests that local banks have different institutional capabilities and strategic aims for technological infrastructure management.

Interesting, credit assessment (mean 3.15), and product sales (mean 3.10) had moderate adoption. These findings partially contradict Njuguna and Kamau (2022), who predicted higher credit assessment adoption rates due to automation's clear benefits in credit risk management and lending efficiency. Kakamega's moderate adoption scores suggest institutional reluctance to automate sensitive lending decisions, insufficient technical capabilities to integrate RPA with complex credit models, or regulatory or internal operational constraints that prevent full-scale automation integration in these sensitive operational areas. As mentioned, sales emphasizes human interaction, which may reduce RPA adoption.

Supply chain and human resource management have lower RPA adoption (mean 2.90 and 2.74, respectively), with high variability (standard deviations 1.71 and 1.74). Despite recent studies predicting HR and supply chain automation, adoption has been low. Wambua and Otieno (2023) suggested automating HR operations including recruitment and payroll to streamline administrative processes. Different strategic priorities among local banks, limited institutional capabilities to implement complex HR automation, or organizational resistance to automation in handling sensitive human resource data, such as job displacement or data privacy, may explain Kakamega's high variability.

Similar to Mutua and Odhiambo (2023), poor adoption in supply chain operations suggests a lack of awareness or skepticism about the viability and security of automation in supply chain management in the Kenyan banking sector.

Inferential study revealed a positive but negligible impact of RPA on Computer Vision applications (β=0.30, p=0.10). This predictor had the highest positive beta coefficient, but its effect was not statistically significant in the insignificant model. This shows that RPA adoption is not a statistically significant predictor of Computer Vision program operational success in this study, despite claimed benefits.'

4.5.4 Utilization of Computer Vision in Document Verification and Identity Authentication

The fourth study objective is to evaluate Computer Vision for document verification and identity identification. The descriptive findings show that computer vision technology is used in commercial banking operations in Kakamega in both prevalent and underutilized ways.

The most popular application was computer vision for real-time monitoring of suspected banking activities, with a mean score of 3.51. Due to the financial and reputational consequences of fraudulent transactions, banks may prioritize real-time fraud protection. Wang et al. (2023) found that real-time anomaly detection is a main use of computer vision in financial institutions, allowing banks to spot irregularities and respond rapidly. The moderate standard deviation (1.30) implies a widespread consensus among respondents about its significance, but slight heterogeneity suggests regional banks may differ in technological competence or strategic focus.

AI-driven facial recognition for identity authentication also had high adoption (mean of 3.46), supporting Maina and Okumu (2022)'s findings that the banking industry is increasingly using facial recognition technologies to improve security, reduce fraud, and streamline customer onboarding. However, the standard variation of 1.41 suggests that privacy concerns, technological challenges in installing effective biometric systems, or growing regulatory compliance issues may prevent certain local institutions from adopting fully.

Automated image analysis for passport and identity card validation was moderately utilized (mean 3.15). This moderate adoption rate supports Chege and Kamau (2022)'s claim that commercial banks are using image-based document verification solutions to eliminate manual errors, improve accuracy, and speed up customer onboarding. However, the large standard deviation (1.50) implies that banks differ in technological capabilities, legacy system integration, and automated document verification system security in Kakamega.

Moderate biometric verification for ATM and branch banking security was also adopted (3.13). This aligns with worldwide banking trends toward biometric physical and digital security. High standard deviation (1.38) may suggest varying implementation and acceptance by banks and clients.

OCR for automated document verification (mean of 2.90) and AI-powered ID verification for account opening and transactions (mean of 2.97) were less popular. OCR underpins many automated document processes, and AI-powered ID verification is essential for digital onboarding and fraud protection, therefore these findings are surprising. The lower uptake may imply that while banks realize the value of these technologies, the implementation obstacles (e.g., integrating with varied document formats, data accuracy, regulatory impediments) may be greater in Kakamega. AI-based fraud detection in identity verification had a mean of 3.00, indicating moderate acceptance. This shows that while banks recognize AI's importance in fraud detection, its use in identity verification may be restricted by data availability and analytical skills in the region.

Computer Vision was the dependent variable in the inferential study, and its regression model linkages with other AI technologies were not statistically significant (ANOVA p=0.29). The regression analysis shows that commercial banks in Kakamega County's adoption of Machine Learning, Natural Language Processing, and Robotic Process Automation does not statistically predict Computer Vision use for automated document verification and identity authentication. This may be because Computer Vision is a younger or more specialized application of AI, or because its adoption is influenced by factors not represented by this study's independent variables.

4.6 Overall Discussion on the Insignificance of the Regression Model

The ANOVA F-test (F=1.29, p=0.29) showing the regression model's non-significance is the most important inferential statistic. This suggests that Machine Learning, Natural Language Processing, and Robotic Process Automation do not statistically explain a significant portion of the variance in Computer Vision applications (our proxy for Operational Performance) in Kakamega County commercial banks. This finding is crucial because it shows that, while individual AI technologies may show varying levels of descriptive adoption or perceived influence in specific banking functions (as discussed in Sections 4.5.1 to 4.5.4), their collective contribution to predicting Computer Vision applications is not statistically significant.

This defies the initial notion that AI technologies will greatly predict operational performance, as supported by much of the literature (Deloitte, 2020; Central Bank of Kenya, 2022). Non-significance in Kakamega could mean numerous things:

1. **Nascent AI Adoption:** Kakamega County commercial banks may be adopting AI early on. Some technologies are being adopted, but they may not be developed enough or widespread enough to have a statistically meaningful impact on operational performance like Computer Vision applications. Instead of systemic, the benefits may be localized to departments or tasks.

2. **The relationship between AI deployment and operational performance** may be indirect. Mediating (e.g., staff training, organizational change management, data quality, specialized regulatory contexts) or moderating (e.g., bank size, IT infrastructure maturity) elements may help turn AI adoption into operational improvements. The regression does not model these parameters, which may explain the lack of statistical significance.

3. **Selective Measure of Dependent Variable: "**Computer Vision applications" may not adequately represent "Operational Performance". Operational performance includes efficiency, cost reduction, accuracy, customer satisfaction, and risk management. Computer Vision contributes to some of these, although it may not fully describe how all AI technologies affect operational effectiveness.

4. **Sample Size and Power:** A 39/40 sample is fine for descriptive analysis, but it may be too small to detect subtle but significant relationships in a regression

model, resulting in non-significant results even if the population has a weak relationship.

5. **Contextual Uniqueness:** Market competition, customer base, regulatory interpretations, and local talent pool may affect how AI technologies are adopted and how they improve performance in Kakamega County's commercial banking landscape, which may differ from more developed or larger markets.

Thus, while the descriptive findings provide valuable insights into AI technology adoption and its perceived influence in various banking functions, the inferential results suggest that, within this research framework and dataset, a clear statistically significant predictive relationship between the chosen AI technologies and Computer Vision applications as a measure of operational performance cannot be established. This underscores the difficulties of quantifying new technology impacts and encourages future study to examine these links more completely and holistically.

CHAPTER FIVE

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.0 Introduction

This chapter summarizes the study's findings on how AI adoption affects commercial banks' operational performance in Kakamega County. These findings are used to draw clear conclusions that address the research objectives. Finally, this study's findings and limitations are used to make practical recommendations for commercial banks and regulators and suggest future research.

5.1 Summary of Findings

The causal-comparative study surveyed 39 Kakamega County commercial bank workers using standardized questionnaires. Machine Learning (ML), Natural Language Processing (NLP), Robotic Process Automation (RPA), and Computer Vision (CV) usage and perceived influence varied among banking functions when descriptive data were examined. In IT, finance, and customer care, ML and RPA were more influential than NLP in marketing and customer service. CV was useful for real-time fraud monitoring and facial identification. All AI technologies had less perceived influence in HRM, supply chain, and credit evaluation.

The model, which included Machine Learning, Natural Language Processing, and Robotic Process Automation as predictors, did not significantly predict Computer Vision applications (a proxy for Operational Performance) using multiple linear regression analysis. An ANOVA F-test p-value of 0.29 above the 0.05 significance criterion. Overall, the independent variables did not affect the dependent variable statistically. Despite some encouraging tendencies, the coefficients for Machine Learning (p=0.32), Natural Language Processing (p=0.48), and Robotic Process Automation (p=0.10) were statistically insignificant. Descriptive findings showed perceived gains in various areas, but the statistical model did not show a meaningful predictive association between AI technology and operational success, as measured by Computer Vision applications.

5.2 Conclusions of the Study

Based on the data, the following conclusions address the research objectives:

1. In Kakamega County, commercial bank employees believe Machine Learning has some impact in IT operations, financial accounting, and customer care for fraud detection and prevention. However, statistical analysis shows that Machine Learning adoption does not significantly predict operational performance (as proxied by Computer Vision applications) in the overall model. This implies that ML implementation in this region may not yet be having a significant statistical influence on operational performance.
2. NLP effectively improves product marketing and customer service channels. Though descriptive in these domains, the study finds that NLP usage does not significantly predict operational performance (Computer Vision applications). NLP enhances specific communication features, but its total contribution to operational efficiency is not statistically significant.
3. RPA enhances efficiency by streamlining financial, accounting, IT, and customer care activities. The statistical evidence reveals that RPA adoption does not significantly predict operational performance (Computer Vision applications) in Kakamega County commercial banks. Despite streamlining

some back-office operations, RPA has not yet had a statistically significant impact on the operational performance metric.

4. Computer Vision is mostly used for real-time suspicious activity monitoring and facial recognition for identity confirmation. The study found no correlation between ML, NLP, and RPA adoption and Computer Vision application use in these institutions. This shows that Computer Vision may be adopted for other reasons or that its integration with other AI technologies is still in its infancy without a clear statistical connection.

In summary, despite the qualitative perception of AI benefits in specific areas, the quantitative analysis shows that the current adoption of Machine Learning, Natural Language Processing, and Robotic Process Automation does not predict overall operational performance (as measured by Computer Vision applications) in commercial banks in Kakamega County. These technologies' effects may be new, localized, or influenced by unknown mediating/moderating factors.

5.3 Recommendations of the Study

According to the study, commercial banks in Kakamega County and stakeholders should adopt a strategic and holistic approach to AI integration, rather than siloed implementations.

1. Banks should create an AI adoption plan that relates AI investments to measurable operational performance measures beyond fraud detection and customer service due to the non-significant overall model. This could involve cross-functional teams identifying end-to-end AI-transformable processes.

2. The lack of significant statistical findings suggests that banks may not have the appropriate data infrastructure or quality for AI models to have a significant influence. Scalable cloud infrastructure, data governance, and data purification should be bank priorities. This is essential for any AI technologies to work and produce results.
3. Targeted Skill Development and Change Management: Improving human capital is necessary due to the variation in adoption and perceived impact across functions. Banks should invest extensively in bespoke training programs for all staff, focused on technical capabilities, AI's strategic value, and change management. For smaller banks with "limited technical expertise and resources," partnerships with local IT institutions or hiring AI consultants for one-month RPA projects to automate HR onboarding tasks may be more realistic.
4. Despite insignificant statistical prediction, descriptive studies suggest experienced benefits. AI should be used to improve high-impact areas like real-time fraud monitoring (using Computer Vision) and consumer communication (using NLP chatbots) locally. While not statistically significant at an operational level, these incremental improvements are vital for competitive advantage and should be built up when effective.
5. To measure the impact of AI, banks should create pilot projects with defined KPIs connected to operational performance. Before broader adoption, pilot RPA in a single back-office operation like loan application processing and carefully measure efficiency improvements (e.g., 30% processing time reduction or 15% error reduction). This shows ROI and learning.

5.4 Recommendations for Further Studies

This study sheds light on AI deployment in commercial banks in Kakamega County, however its limitations suggest several topics for further research:

1. Future studies should consider mediating and moderating variables related to AI adoption and operational performance, such as employee training and acceptance, data quality, organizational culture, regulatory compliance, and bank size, IT budget, and years of digital transformation efforts, as the relationship between AI adoption and operational performance is not statistically significant. This would clarify how and when AI adoption affects operations.
2. This cross-sectional study offers a picture of longitudinal and qualitative studies. Longitudinal studies could track AI adoption and its effects across time, including implementation maturity and long-term benefits. Additionally, in-depth qualitative case studies of particular banks could reveal the challenges, triumphs, and unique contextual elements affecting AI adoption and operational outcomes.
3. This study proxied operational performance with Computer Vision applications. Future research should include comprehensive and multi-dimensional operational performance metrics like cost efficiency, service delivery speed, customer satisfaction scores, risk reduction, and competitive advantage, validated by objective data (where possible) and perceptual measures.
4. To determine if findings are specific to Kakamega County, future research might compare findings across Kenya or East Africa, or between large national

banks and smaller regional banks. This would assist generalize findings and identify regional or organizational AI impact variables.

Further research might examine the ROI of specific AI use cases in banking, such as automated compliance checks, tailored financial advising, or enhanced credit scoring. Banks would have greater data for strategic investment decisions.

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APPENDICES

Appendix I: Consent Letter

To Whom It May Concern,

I, **Matseshe Sadam Yamboko**, am a student of the Master in Business Administration program at **Mount Kenya University**. As part of the partial fulfillment of the degree requirements, I am conducting a research study titled, **"Influence of Artificial Intelligence Technologies Adoption on the Operational Performance of Commercial Banks in Kakamega Town, Kakamega County, Kenya."**

The purpose of this research is to explore how the adoption of Artificial Intelligence (AI) technologies has affected the operational performance of commercial banks located in Kakamega Town, Kakamega County. The study focused on assessing how these technologies impact efficiency, customer satisfaction, decision-making, and the overall performance of the banks.

I am writing to seek your consent and approval for your participation in this study. Your input and feedback are invaluable in helping me understand the influence of AI adoption in the banking sector. Please be assured that participation in this research is voluntary, and you have the right to withdraw at any stage without any negative consequences. All data collected was treated with the utmost confidentiality, and results were used solely for academic purposes.

If you are willing to participate in the study, please indicate your consent by signing the attached consent form. Your participation contributed significantly to the success of this research.

Should you have any questions or require further clarification regarding this study, feel free to contact me via email or phone.

I appreciate your time and consideration in supporting my research.

Consent Form

I, the undersigned, hereby consent to participate in the research titled, "Influence of Artificial Intelligence Technologies Adoption on the Operational Performance of Commercial Banks in Kakamega Town, Kakamega County, Kenya."

I understand that my participation is voluntary, and I can withdraw from the study at any time without any negative consequences. I also understand that the data collected will be treated with confidentiality and used for academic purposes only.

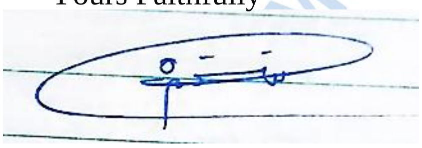
Name: ___________________________

Signature: ________________________

Date: ___________________________

Thank you for your cooperation.

Yours Faithfully



Matseshe Sadam,

P.O Box 525-5012,

Mumias, Kenya.

+254 704 667 381

Appendix II: Questionnaire

Instructions

This project aims to collect data on the effects of AI technology adoption on the operational performance of commercial banks in Kakamega County, Kenya. The gathered data will be utilized solely for academic purposes and maintained in absolute confidentiality. Kindly complete this survey in its entirety and with impartiality.

Select the relevant checkbox to signify your response. Kindly provide comprehensive responses to inquiries necessitating elaboration in the specified blank areas. If additional room is needed for your responses, please use the section at the back of this survey.

SECTION A: BACKGROUND INFORMATION

1. Gender: Male [ ] Female [ ]
2. What are your age brackets? Under 30 Years [ ] 31 to 35 Years [ ] 36 to 40 years [ ] 41 to 45 Years [ ] 46 to 50 years Exceeding five decades [ ]
3. What is the greatest level of education you have completed? Diploma [ ] Master's [ ] Degree: [ ] PhD [ ] Other Specifications………………….
4. What is the duration of your employment with the organization? Fewer than twelve months [ ] 1 to 3 years [ ] 4 to 7 years 8 years and older [ ]
5. What is your role inside the organization? Branch Manager [ ] Operations Manager [ ] Information Technology Manager [ ]
6. For how long have you occupied your current position? Fewer than twelve months [ ] 1 to 3 years [ ] 4 to 7 years 8 years and older [ ]

SECTION B: ARTIFICIAL INTELLIGENCE

This segment comprises three components: machine learning, robotic process automation, and natural language processing.

Machine Learning

7. To what degree does the organization employ machine learning to maintain its competitive edge? (Kindly select one option)
    a) Not at all [ ]
    b) To a minor extent [ ]
    c) To a moderate degree [ ]
    d) To a significant degree [ ]
    e) To a significant degree [ ]
8. To what extent does the bank employ each of the following machine learning options in response to market fluctuations? Utilize 1- No extend. To a minor extent, 3 - Moderate extent, 4 - Significant extent, 5 - Extensive extent

Element	1	2	3	4	5
The bank has implemented robotic process automation in credit assessment.					
The bank employs robotic process automation for selling its products.					
The bank employs robotic process automation throughout its supply chain.					

The bank employs robotic process automation in human resource management.
The bank employs robotic process automation in its IT operations.
The bank employs robotic process automation in its customer care operations.
The bank employs robotic process automation in its financial and accounting operations.

Natural Language Processing

9. To what degree does the bank employ natural language processing to maintain its competitive edge? (Please select one)
   a) Not at all ( ) b) To a little degree ( )
   b) To a moderate degree ( )
   c) To a significant degree ( )
   d) To an extensive degree ( )
10. What is the significance of the following in informing natural language processing at ABSA? Utilize 1 - No extent, 2 - Minimal extent, 3 - Moderate extent, 4 - Significant extent, 5 - Extensive extent

Element	1	2	3	4	5

The bank has implemented natural language processing in credit assessment.
The bank use natural language processing for marketing its products.
The bank employs natural language processing within its supply chain.
The bank employs natural language processing in human resource management.
The bank employs natural language processing throughout its information technology operations.
The bank employs natural language processing in its customer service operations.
The bank employs natural language processing in its financial and accounting operations.

Robotic Process Automation

11. To what degree does ABSA employ robotic process automation to gain a competitive advantage? (Kindly select one option)

    a) Not at all ( )

b) To a minor extent ( )

c) To a moderate degree ( )

d) To a significant degree ( )

e) To a significant degree ( )

12. Evaluate the extent of implementation of the subsequent robotic process automation initiatives at the bank. Utilize 1 - No extent, 2 - Minimal extent, 3 - Moderate extent, 4 - Significant extent, 5 - Extensive extent

Element	1	2	3	4	5
The bank has implemented robotic process automation in credit assessment.					
The bank employs robotic process automation for selling its products.					
The bank employs robotic process automation throughout its supply chain.					
The bank employs robotic process automation in human resource management.					
The bank employs robotic process automation in its information technology operations.					

The bank employs robotic process automation in its customer care operations.	
The bank employs robotic process automation in its financial and accounting operations.	

Examining the Applications of Computer Vision for Automated Document Verification and Identity Authentication in Commercial Banking Transactions

Computer Vision Element	**1**	**2**	**3**	**4**	**5**
The bank uses AI-driven facial recognition for identity authentication.					
The bank employs OCR (Optical Character Recognition) for automated document verification.					
The bank utilizes AI-powered ID verification for account opening and transactions.					
The bank integrates biometric verification for ATM and branch banking security.					
The bank applies AI-based fraud detection in identity verification					

processes.

The bank uses automated image analysis to validate customer-submitted documents.

The bank employs computer vision for real-time monitoring of suspicious banking activities.

Would you like any refinements or additional elements included?

SECTION C: Operational Performance

13. To what degree has the following enhanced at the Bank? Utilize 1 - No extent, 2 - Minimal extent, 3 - Moderate extent, 4 - Significant extent, 5 - Extensive extent

Elements	**1**	**2**	**3**	**4**	**5**
Total deposits					
Profitability					
Total loans					
Banking establishments					

Client cultivation
Expansion of assets
Market share
Operational efficacy

Appendix III: Interview Guide

Section A: General Information

What AI-based fraud detection measures are currently implemented in your bank?

. . . .

How effective have machine learning algorithms been in identifying fraudulent transactions?

. . . .

What types of fraud are most commonly detected using AI in your bank?

. . . .

What challenges have you faced in implementing machine learning for fraud prevention?

. . . .

What improvements do you think are needed to enhance AI-driven fraud detection systems?

. . . .

Investigating the Effectiveness of Natural Language Processing in Improving Customer Service and Communication Channels in Commercial Banking

Does your bank utilize AI-powered chatbots or virtual assistants for customer service?

. . . .

How has NLP technology impacted customer interactions and response times?

. . . .

What are the most common customer queries handled by AI-driven communication tools?

. . . .

Have you observed any resistance from customers in using AI-based customer service solutions?

. . . .

What strategies could improve the efficiency and adoption of NLP technologies in customer service?

. . . .

Evaluating the Role of Robotic Automation in Enhancing Operational Efficiency and Streamlining Back-Office Processes in Commercial Banks

Has your bank adopted Robotic Process Automation (RPA) in any of its operations? If so, in what areas . . . .

. . . .

How has RPA contributed to operational efficiency, cost reduction, or error minimization?

. . . .

What specific banking processes have benefited the most from automation?

. . . .

What challenges have been encountered in integrating RPA into banking operations?

. . . .

What recommendations do you have for improving RPA adoption and effectiveness in commercial banks?

. . . .

Examining the Applications of Computer Vision for Automated Document Verification and Identity Authentication in Commercial Banking Transactions

Is computer vision technology used in your bank for document verification and identity authentication? If so, how? . . . .

. . . .

How has the adoption of computer vision affected transaction security and fraud prevention? . . . .

. . . .

What types of documents are currently verified using AI-driven systems? . . . .

. . . .

What challenges or limitations have you faced in implementing AI-driven identity verification? . . . .

. . . .

What future developments do you foresee in the application of computer vision in commercial banking?

. . . .

Appendix IV: ERC Letter

Mount Kenya University

REF: **MKU/ISERC/5005**

Date: 24 April 2025

TO: **MATSESHE SADAM YAMBOKO**

REG: **MBA/2023/49726**

Dear Sir/Madam,

RE: INFLUENCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES ADOPTION ON THE OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS IN KAKAMEGA TOWN, KAKAMEGA COUNTY, KENYA.

This is to inform you that **Mount Kenya University** has reviewed and approved your above research proposal. Your application approval number is **3727.** The approval period is **24/04/2025 - 23/04/2026.**

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 **Mount Kenya University**
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 **Mount Kenya University** within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to **Mount Kenya University** 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 **Mount Kenya University**

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. Alfred Owino, PhD
Chairman, Mount Kenya University ISERC

MOUNT KENYA UNIVERSITY
ETHICS REVIEW COMMITTEE
P. O. Box 342 - 01000,
THIKA

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Chartered and ISO 9001 : 2015 Certified

Appendix V: Introduction Letter

Mount Kenya University

DIRECTORATE OF GRADUATE STUDIES

MBA/2023/49726

28th April, 2025

National Commission for Science Technology & Innovation (NACOSTI)
Off Waiyaki Way, Upper Kabete,
P.O Box 30623- 00100
NAIROBI, KENYA

Dear Sir/Madam,

RE: MATSESHE SADAM YAMBOKO – REGISTRATION NO. MBA/2023/49726

The purpose of this letter is to introduce the above named student who is pursuing **Master of Business Administration** in the department of **Accounting and Finance** in the school of **Business and Economics.**

The title of the research is **"Influence of Artificial Intelligence Technologies Adoption on the Operational Performance of Commercial Banks in Kakamega Town, Kakamega County, Kenya."** It has been cleared by the University's Ethics Review Committee (Certificate attached) and now has to proceed to the field to collect data between **May, 2025 and July, 2025.**

Any assistance accorded to the student will be highly appreciated.

Thank you.

Mount Kenya University
P.O. Box 342 - 01000.THIKA
Office of the Director,
Graduate Studies

Dr. Samuel M. Karenga, PhD
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Appendix VI: NACOSTI Authorization

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **967185**

Date of Issue: **14/May/2025**

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This is to Certify that Mr.. MATSESHE SADAM YAMBOKO of Mount Kenya University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kakamega on the topic: INFLUENCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES ADOPTION ON THE OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS IN KAKAMEGA TOWN, KAKAMEGA COUNTY, KENYA. for the period ending : 14/May/2026.

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Appendix VII: Similarity Index

MATSESHE SADAM YAMBOKO

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