EFFECT OF AI ADOPTION ON THE ORGANIZATIONAL PERFORMANCE OF INSURANCE COMPANIES IN KENYA

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

In the current dynamic and volatile business environment, many organizations struggle with outdated systems, inefficient processes, and inability to meet customer demands swiftly (Kendall, 2019). Most firms continue to face declining productivity due to reliance on manual processes and outdated machinery. Such inefficiencies not only impact operational costs but also hinder adaptability to market changes, fostering a pressing need for innovative solutions. As firms grapple with these challenges, technology adoption thus emerges as a pivotal strategy. Technologies such as Artificial Intelligence (AI) offer transformative potential by automating routine tasks, enhancing decision-making capabilities, and improving overall operational efficiency. Johnson (2019) illustrates how AI-driven predictive analytics can optimize supply chain management, reducing inventory costs and enhancing responsiveness to customer demands. Empirical evidence underscores the positive impact of AI adoption on firm performance across various sectors. Lee and Kim (2022) found that financial institutions integrating AI into customer service operations experienced higher customer satisfaction levels and operational efficiencies.

AI technologies have thus been increasingly integrated into insurance operations, enhancing efficiency, customer experience, and risk management capabilities (Kendall, 2019). In the United States, Progressive Insurance utilizes AI-powered chatbots to handle customer inquiries and claims processing, thereby reducing response times and improving customer satisfaction (Smith, 2020). Similarly, in Japan, Fukoku Mutual Life Insurance has implemented AI systems for processing insurance claims, resulting in a significant reduction in operational costs and improved accuracy (Miyamoto et al., 2019). These examples highlight AI's transformative potential in enhancing operational efficiencies and service delivery within the insurance industry. In Europe, AI adoption in insurance extends to predictive analytics and underwriting processes. Companies like Allianz and AXA have leveraged AI algorithms to analyze vast datasets and predict customer behaviour and risk profiles more accurately (Kaiser, 2021).

By automating underwriting decisions, insurers can offer more personalized policies and streamline risk assessment processes. This approach not only improves profitability but also enhances customer satisfaction by tailoring insurance products to individual needs based on real-time data insights. Additionally, in Asia, particularly in Singapore, AI technologies are utilized to detect insurance fraud more effectively. Companies such as NTUC Income, Singapore's leading provider of Life, Health, Travel & Car Insurance as well as savings, investment and retirement plans, have deployed AI-driven fraud detection systems that a nalyze transaction patterns and behavioral anomalies to identify potentially fraudulent activities (Nguyen et al., 2022). This proactive approach not only mitigates financial losses but also safeguards the integrity of insurance operations, thereby reinforcing trust among policyholders and stakeholders. In Latin America, AI adoption in insurance has focused on enhancing digital engagement and customer interaction. Insurtech startups like Seguros SURA in Colombia have integrated AI-powered virtual assistants to provide instant policy quotes, assist with claims processing, and offer personalized insurance recommendations (Gonzalez, 2023).

However, while AI promises significant benefits, its successful implementation requires overcoming barriers such as data privacy concerns, regulatory compliance issues, and organizational resistance to change (Davis, 2023). In Kenya, AI adoption in the insurance sector is nascent but promising. Companies like Jubilee Insurance have begun exploring AI applications in customer service automation and data analytics to enhance operational efficiencies (Odhiambo, 2021). Challenges such as data privacy concerns, regulatory frameworks, and infrastructure limitations pose barriers to widespread AI adoption in the region. Despite these challenges, initiatives are underway to leverage AI's potential to expand insurance coverage, improve risk management, and enhance customer experiences in Kenya's evolving insurance landscape. Addressing these concerns through effective change management strategies and continuous training is crucial for maximizing AI's potential hence the need for this study.

The Kenyan insurance market, encompassing both life and non-life segments, provides a range of products such as health, motor vehicle, and property insurance, tailored to various socio-economic groups. Key operations include risk assessment, premium determination, and claims management, all regulated by the Insurance Regulatory Authority (IRA) to maintain market stability and protect consumers (Odhiambo &

Nyamongo, 2020). Despite technological advancements improving efficiency, challenges like low penetration rates, particularly in rural areas, persist, with innovations like mobile-based insurance and microinsurance showing promise in enhancing financial inclusion (Kibet & Koskei, 2021; Ochieng & Oluoch, 2022). The adoption of AI in the sector has the potential to further revolutionize underwriting, claims processing, and customer engagement, potentially driving greater efficiency, accuracy, and personalized service delivery, thereby improving overall market penetration and customer satisfaction.

AI adoption refers to the integration of artificial intelligence technologies into business processes to enhance efficiency, decision-making, and innovation (Russell, 2020). This operationalization involves developing AI algorithms that can analyze vast amounts of data to derive insights and automate tasks traditionally performed by humans (Binns, 2018). In measuring AI adoption, organizations often assess its effectiveness in improving operational efficiencies and achieving strategic objectives. For example, in healthcare, AI-powered diagnostic tools have shown promise in enhancing accuracy and reducing diagnostic errors (Topol, 2019). Metrics such as cost savings, productivity gains, and customer satisfaction are commonly used to quantify the impact of AI adoption on business performance (Varian, 2019). This approach helps firms gauge the return on investment (ROI) of AI initiatives and justify further resource allocation towards AI development and implementation.

In terms of insurance practices, AI adoption is revolutionizing customer service and risk management. Companies like Lemonade, America's top-rated insurance company, have leveraged AI chatbots to streamline claims processing and improve response times (Kuo, 2021). AI algorithms can analyze customer data to personalize insurance products and pricing, enhancing customer satisfaction and retention (Lloret-Gallego et al., 2020). Moreover, AI-driven predictive analytics enable insurers to assess risks more accurately, leading to better underwriting decisions and reduced claims fraud (Jiang et al., 2022). Critically assessing the literature on AI adoption reveals challenges such as ethical considerations and the potential for job displacement. Scholars argue that while AI offers efficiency gains, its deployment raises ethical concerns regarding data privacy, bias in algorithmic decision-making, and the societal impact of automation on employment (Etzioni and Etzioni, 2021). For instance, AI algorithms may inadvertently perpetuate discriminatory practices if not properly monitored and regulated (Crawford et al., 2019).

Moreover, the displacement of certain job roles by AI technologies underscores the need for proactive workforce reskilling and policy frameworks to mitigate negative social Effects (Manyika et al., 2020). Examples from the financial sector illustrate both the promise and challenges of AI adoption. Banks like JPMorgan Chase use AI algorithms to detect fraud more effectively, leveraging machine learning to analyze transaction patterns and identify suspicious activities in real-time (Fernández et al., 2020). However, concerns about algorithmic bias and the interpretability of AI models persist, prompting calls for transparency and accountability in algorithmic decision-making processes (Barocas and Selbst, 2016). These issues underscore the importance of ethical guidelines and regulatory frameworks to ensure responsible AI deployment across industries.

AI's role in improving customer satisfaction is evident in its ability to offer personalized and efficient service. According to a study by Deloitte (2019), AI enables companies to analyze vast amounts of customer data, allowing for the creation of tailored experiences that meet individual customer needs. This personalization leads to higher customer satisfaction, as services and products are aligned more closely with consumer preferences. This is clear in sectors that leverage its ability to deliver personalized and efficient services, yet this remains significantly underutilized in Kenyan insurance firms. In Kenya, most insurers still rely on traditional methods, resulting in delayed claim processes, generalized customer interactions, and poor responsiveness. The limited integration of AI-driven solutions like chatbots, predictive analytics, and automated customer service has contributed to a disconnect between customer expectations and the services offered. Consequently, customers often experience dissatisfaction due to slow responses, lack of tailored products, and inadequate engagement, highlighting the gap in AI adoption within Kenya's insurance industry (McKinsey, 2020).

In contrast, firms that have been slow to adopt AI struggle to meet modern consumer expectations, as customers increasingly demand real-time responses and customized solutions (Brynjolfsson & McAfee, 2017). The situation is even more pronounced in developing countries such as Kenya, where AI-driven customer service platforms are revolutionizing how businesses engage with consumers. A study by the Communications Authority of Kenya (2021) highlights how AI adoption in the telecom sector has significantly improved customer experience by reducing response times and offering more personalized service, thereby increasing customer satisfaction in a competitive market. Efficiency gains from AI adoption are another critical aspect that contributes to enhanced organizational performance. AI systems can process large volumes of data more quickly and accurately than humans, leading to more efficient operations.

According to a report by Accenture (2017), businesses that have implemented AI-driven automation have seen productivity improvements of up to 40%. This is echoed by findings from the World Economic Forum (2018), which indicate that AI's ability to optimize supply chains, manage inventory, and predict maintenance needs has reduced operational costs and increased efficiency across various industries. In developing countries, particularly in Africa, AI adoption has shown promise in addressing inefficiencies in sectors such as agriculture and healthcare. For instance, AI-driven platforms in Kenya have been used to optimize farming practices by predicting weather patterns and advising on best planting times, leading to increased crop yields and reduced waste (Ndung'u, 2020). These efficiency gains not only enhance business performance but also contribute to broader economic growth in these regions.

Despite the clear benefits, the adoption of AI also presents challenges that can impact customer satisfaction and efficiency. One significant challenge is the digital divide, particularly in developing countries where access to advanced technologies is limited. A report by the International Telecommunication Union (ITU, 2020) notes that while AI has the potential to transform industries, its adoption in Africa is hindered by inadequate infrastructure and lack of skilled personnel. This creates a disparity in performance gains between companies in developed and developing countries. In Kenya, for instance, while some sectors have benefited from AI, others, particularly in rural areas, remain untouched by this technological revolution (Mwakaba, 2019). This uneven adoption can lead to inefficiencies and customer dissatisfaction in regions where AI is not yet fully integrated. Furthermore, ethical concerns around AI, such as data privacy and job displacement, can also impact customer trust and satisfaction. Consumers are becoming increasingly aware of how their data is used, and any misuse or perceived lack of transparency can erode trust, ultimately affecting customer satisfaction (Binns, 2018).

The comparative analysis of AI adoption between developed and developing countries reveals a complex picture of performance enhancement. In developed nations, the widespread integration of AI has led to significant improvements in both efficiency and customer satisfaction, as noted by various studies (Brynjolfsson & McAfee, 2017; McKinsey, 2020). However, in developing countries like Kenya, while there are pockets of success, the overall impact of AI on performance is uneven. The barriers to adoption, such as infrastructure deficits and skills shortages, limit the ability of businesses in these regions to fully realize the benefits of AI. Nevertheless, the potential for AI to drive performance improvements in these countries remains high, particularly as infrastructure improves and more organizations begin to embrace AI technologies (Ndung'u, 2020). The key to maximizing the impact of AI on performance, especially in developing regions, lies in addressing these barriers and ensuring that AI adoption is inclusive and equitable across all sectors.

1.2 Research Problem

The insurance sector in Kenya has been grappling with significant challenges leading to poor performance and efficiency in recent years. Several prominent insurers have faced financial distress or dissolution due to mismanagement and inadequate risk assessment practices (Munyao, 2020). Concord Insurance Company Limited and United Insurance Company are notable examples where financial missteps and regulatory non-compliance led to their closure (IRA, 2021). Furthermore, customer dissatisfaction has been on the rise, marked by increasing complaints related to claims processing delays and disputes over policy coverage. According to the Insurance Regulatory Authority (IRA), grievances over poor service delivery and opaque policy terms have strained consumer trust in insurers (IRA, 2021). This trend reflects broader operational inefficiencies and regulatory gaps that undermine consumer protection measures mandated by the IRA.

In response to these challenges, the adoption of artificial intelligence (AI) technologies has emerged as a potential remedy to enhance operational efficiency and customer satisfaction in the insurance sector. AI offers capabilities such as predictive analytics for risk assessment, automated claims processing, and personalized customer interactions (Kendall, 2019). These technologies aim to streamline operations, reduce administrative costs, and improve decision-making accuracy. However, the impact of AI adoption in the insurance sector remains nuanced and subject to diverse empirical findings. Research indicates that AI can indeed optimize underwriting processes and detect fraudulent claims more effectively than traditional methods (KPMG, 2022). AI-driven algorithms can analyze large datasets to identify patterns indicative of fraudulent behavior, thereby reducing financial losses for insurers (Nass, 2020). Such technological advancements have the potential to transform risk management practices and enhance profitability in the long term.

Despite these advancements, the integration of AI into insurance operations poses challenges and uncertainties. Studies highlight varying outcomes and mixed results regarding AI's effectiveness in mitigating broader systemic issues within the sector. Some researchers argue that while AI can improve efficiency in specific domains, its implementation requires substantial investment in infrastructure and skilled personnel (Bannister & Connolly, 2018). Moreover, regulatory compliance and ethical considerations surrounding AI deployment remain critical concerns for insurers and policymakers alike (EY, 2021). Thus, while AI holds promise for addressing the inefficiencies plaguing Kenya's insurance sector, its transformative impact is contingent upon overcoming implementation challenges and regulatory hurdles, hence the need for this study. The study will aim to fill the research gaps and address the research question: what are the effects of AI adoption in the insurance sector in Kenya?

1.3 Research Objectives

The general objective of the study was to investigate the effects of AI adoption on organizational performance in the insurance sector in Kenya

The study was guided by the following specific research objectives:

i. To determine the extent to which the insurance companies have adopted AI Technology.

ii. To investigate the effect of AI adoption on insurance company performance as proxied by customer satisfaction and efficiency.

1.4 Research Questions

The study aimed at addressing the following research questions:

i. What percentage of operations in the Kenyan insurance sector are AI-driven?

ii. What is the effect of AI adoption on aspects of processing in the insurance sector in Kenya?

iii. What is the effect of AI adoption on insurance company performance as proxied by customer satisfaction and efficiency?

1.5 Significance of the Study

Integrating AI into Kenya's insurance sector could revolutionize policy frameworks. Policymakers can leverage AI-driven insights to enhance regulatory practices, such as more accurate risk assessment models, fraud detection algorithms, and personalized pricing strategies. This adoption can lead to the formulation of policies that promote innovation while ensuring consumer protection and market stability. For instance, by analyzing vast datasets in real-time, AI can help regulators promptly identify emerging risks, thereby enabling proactive policy adjustments. Moreover, policies can be designed to incentivize AI adoption among insurers, fostering a competitive landscape that benefits both insurers and consumers. In practice, AI adoption promises transformative Effects on how insurance products are designed, marketed, and serviced in Kenya. Insurers can deploy AI-powered chatbots and virtual assistants to enhance customer service experiences, providing instant responses and personalized recommendations based on customer data. Claims processing can become more efficient through AI algorithms that automate claim validation and settlement processes, reducing processing times and operational costs. Additionally, AI's predictive analytics capabilities can enable insurers to develop innovative insurance products tailored to the evolving needs of Kenyan consumers, such as micro-insurance solutions for low-income segments.

From a theoretical perspective, AI adoption in Kenya's insurance sector can generate new insights. Scholars can explore how AI influences consumer behaviour, decision-making processes, and market dynamics within the insurance industry. Theories on technological innovation and organizational change can be expanded to incorporate AI-driven disruptions and adaptations. Moreover, AI's impact on risk management theories can be studied to understand how predictive analytics and machine learning algorithms redefine risk assessment methodologies. Theoretical frameworks can also evolve to analyze the ethical implications of AI adoption, such as data privacy concerns and algorithmic bias, ensuring a balanced approach to technological integration in insurance practices. The study will further form basis for which further studies will be undertaken.

1.6 Scope of the Study

The scope of this study encompassed investigation into the adoption and effects of artificial intelligence (AI) in Kenya's insurance sector, focusing on specific objectives. The scope of this study covers the adoption and impact of artificial intelligence (AI) across all 56 licensed general insurance firms in Kenya, gathering secondary data for the past 5 years (2019-2023). The study adopted a descriptive research design where study collected data using questionnaires and analysed using descriptive and inferential analysis.

1.7 Organization of the Study

This project was organized in three chapters: Chapter one is comprised of the background of the study, statement of the problem, research objectives, research questions, significance, scope, and organization of the study. Chapter two was on the literature review, the theoretical framework, and the conceptual framework. Whereas chapter three consisted of the research design and methodology, data collection procedures and data analysis techniques.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The relevant literature review linked to the study objectives is included in this part. The chapter analyzed previous studies that have been undertaken that are pertinent to the investigation. The conceptual framework for examining the relationships between the dependent and independent variables is also covered in this chapter. The chapter finalizes with the research gaps.

2.2 Artificial Intelligence

Artificial Intelligence (AI) refers to the capability of machines to mimic cognitive functions such as learning, problem-solving, and decision-making, which are typically associated with human intelligence. AI encompasses a broad range of subfields including machine learning, natural language processing, robotics, and expert systems, each contributing to its broad applicability. According to Makridakis (2017), AI is defined as the simulation of human intelligence processes by computer systems. These processes include learning, reasoning, and self-correction, enabling the systems to improve over time. Machine learning involves training algorithms to identify patterns and make data-driven decisions, while natural language processing focuses on enabling machines to understand and generate human language (Goodfellow, Bengio, & Courville, 2016). Consequently, AI is reshaping organizational practices by optimizing operations and enhancing decision-making processes, thereby offering a competitive advantage in an increasingly digital landscape (Agrawal, Gans, & Goldfarb, 2018).

AI encompasses a wide array of components that together drive its functionality and operationalization. These include data analytics, algorithms, neural networks, and advanced computing systems that enable machines to perform tasks with minimal human intervention. Machine learning, a critical element of AI, involves algorithms that improve their performance through experience, enabling systems to make accurate predictions or decisions based on historical data (Jordan & Mitchell, 2015). Additionally, deep learning, a subset of machine learning, employs artificial neural networks with multiple layers to analyze complex data patterns, further enhancing AI's capabilities (LeCun, Bengio, & Hinton, 2015). These advanced AI mechanisms are pivotal in automating processes, particularly in sectors like healthcare, finance, and insurance, where they are utilized for tasks such as risk assessment, fraud detection, and customer service automation. As AI continues to evolve, its integration into organizational operations has become increasingly seamless, reducing operational costs and enhancing efficiency (Brynjolfsson & McAfee, 2017). Therefore, the operationalization of AI within organizations is not limited to technical deployments but extends to strategic implementations that align AI systems with business goals and industry standards (Rai, 2020).

The application of AI is diverse and spans across various industries, providing innovative solutions that drive business growth. In the insurance sector, AI technologies are extensively utilized to streamline operations and enhance customer experiences. For instance, AI-driven chatbots and virtual assistants are deployed to handle customer inquiries, providing instant responses and improving service delivery (Brock & Wangenheim, 2019). Additionally, machine learning algorithms are employed in risk assessment and underwriting processes, allowing insurance firms to analyze large datasets and make informed decisions more efficiently (Davenport & Ronanki, 2018). In claims management, AI models are used to detect fraudulent claims by analyzing patterns that deviate from the norm, thereby reducing potential losses (Baesens et al., 2016). Moreover, predictive analytics powered by AI assists insurance companies in forecasting trends, enabling proactive decision-making and personalized policy offerings that cater to individual customer needs (Gartner, 2020). Consequently, AI has become a key driver of innovation in the insurance industry, providing firms with tools that enhance operational efficiency while offering competitive advantages in a rapidly changing market environment (Ernst & Young, 2019).

AI's applicability within organizations is not limited to process automation but extends to strategic decision-making and innovation management. In insurance companies, for example, AI is utilized to analyze vast amounts of data, providing actionable insights that inform product development and market positioning. By integrating AI into their operations, these firms can better understand customer behaviors and preferences, allowing them to tailor products and services to meet evolving demands (Chen, Chiang, & Storey, 2012). Furthermore, AI is leveraged in developing advanced pricing models that factor in a wide range of variables, ensuring more accurate risk assessments and premium calculations (Mills, 2019). AI also plays a crucial role in customer retention strategies by enabling personalized engagement, where predictive algorithms identify customers at risk of churn and trigger targeted interventions (Sivarajah et al., 2017). As such, AI's integration within insurance companies is not merely a technological upgrade but a strategic shift towards data-driven business models that prioritize efficiency, customer satisfaction, and competitive positioning (Venkatesh et al., 2021). This shift underscores the relevance of AI in enhancing both operational and strategic functions, ultimately contributing to sustained organizational growth and market relevance (Brynjolfsson et al., 2018).

AI’s growing presence in the insurance industry exemplifies how organizations are capitalizing on advanced technologies to drive operational efficiencies and maintain competitive advantage. One notable application is in customer service, where AI-powered tools like chatbots enhance responsiveness and service quality by providing real-time support (Manning & Preston, 2020). Additionally, AI is applied in personalized marketing efforts, where data analytics tools assess customer profiles and behaviors to design targeted campaigns that resonate with specific segments (Huang & Rust, 2018). Insurance companies are also leveraging AI in fraud detection, using pattern recognition and anomaly detection algorithms to identify potentially fraudulent claims, thereby mitigating risks and improving profitability (Klein, 2020). Moreover, AI facilitates regulatory compliance by automating complex reporting processes and ensuring adherence to industry standards, which is particularly beneficial in highly regulated sectors like insurance (Sun, 2018). These examples highlight AI’s multifaceted role in transforming traditional business models, enabling organizations to optimize operations, enhance customer satisfaction, and sustain competitive advantages in increasingly dynamic markets (Baryannis et al., 2019).

2.3 Organizational performance

Organizational performance is a broad concept that captures the efficiency and effectiveness with which a company meets its objectives. According to Mishra and Misra (2019), organizational performance encompasses the ability of a firm to achieve its objectives by aligning resources and strategic decisions to ensure competitiveness in the market. Typically, performance is evaluated based on financial measures such as profitability and revenue growth, alongside non-financial indicators like customer satisfaction and employee engagement (Gavrea et al., 2020). The multidimensional nature of performance also accounts for how well an organization adapts to environmental changes while still maintaining sustainable practices (Jain & Ansari, 2018). In the insurance industry, organizational performance often revolves around metrics like claim processing times, customer retention rates, and compliance with regulatory standards, which are critical in determining a firm's market position.

Operationalizing organizational performance requires breaking it down into measurable components that align with strategic objectives. The process involves identifying key performance indicators (KPIs) that reflect both financial and non-financial outcomes (Quesado et al., 2018). For instance, in insurance firms, KPIs might include the loss ratio, which measures the proportion of claims paid out relative to premiums earned, and the expense ratio, which indicates operational efficiency. Kalyani (2019) argues that performance measurement should be dynamic, reflecting not just immediate financial results but also long-term sustainability. In this context, insurance firms must balance profitability with client satisfaction, regulatory compliance, and market competitiveness. Albrecht et al. (2019) note that performance can also be operationalized through balanced scorecards, which incorporate financial, customer, internal processes, and learning and growth perspectives to give a holistic view of how well an organization is performing. The balance between financial outcomes and qualitative aspects like customer loyalty and employee satisfaction is crucial for the overall health of a company, particularly in industries where service quality is as vital as profitability.

The concept of organizational performance is applicable across various sectors, including insurance, where it plays a vital role in determining competitive advantage. In insurance, operational efficiency, client satisfaction, and market adaptability are central to performance metrics (Hussain et al., 2018). The practical application of performance management frameworks like Total Quality Management (TQM) in insurance companies underscores how these concepts can be tailored to industry-specific needs. Additionally, digital transformation in the insurance sector has introduced new dimensions to organizational performance, such as digital customer engagement and automated claim processing, which have become critical for maintaining market share (Ikram et al., 2020). Through such strategic alignment and innovation, insurance firms can sustain long-term profitability and customer loyalty, both of which are key indicators of high organizational performance.

Organizational performance entails a range of factors including financial health, operational efficiency, and adaptability to change, all of which are interrelated and must be carefully managed to achieve strategic objectives. Performance frameworks like the Balanced Scorecard are often used to link organizational strategy with measurable outcomes (Kaplan & Norton, 2020). These frameworks emphasize a balance between financial objectives and non-financial metrics, such as customer satisfaction and internal process efficiency, which are particularly relevant in the service-oriented insurance industry. Moreover, performance in insurance firms is heavily influenced by external factors such as economic conditions, regulatory changes, and technological advancements, making adaptability a key aspect of success (Mohd et al., 2021). Studies suggest that firms which align their performance measurement systems with both strategic goals and market dynamics tend to outperform their peers in terms of profitability, customer loyalty, and market expansion (Njoroge & Omagwa, 2019). Therefore, integrating strategic management principles with performance monitoring tools is essential for sustaining competitive advantage in dynamic sectors like insurance.

The examples of organizational performance measurement in insurance companies highlight how these firms operationalize their strategies to meet both financial and customer-related objectives (Wang et al., 2021). By continuously refining their performance metrics to align with changing customer expectations and market trends, these firms have maintained leadership in their respective markets. Research also points out that the introduction of InsurTech solutions, such as AI-driven customer service platforms, has significantly enhanced operational efficiency and, by extension, overall performance (Rahman et al., 2020). These innovations allow for faster claim processing, personalized customer interactions, and better risk management, thereby boosting both customer satisfaction and financial performance. The adaptability and responsiveness demonstrated by these firms underscore the importance of dynamic performance management in maintaining competitive positioning in a rapidly evolving market.

From the above literature, organizational performance is commonly assessed through a combination of financial and non-financial measures. Financial measures such as profitability, revenue growth, and return on investment provide direct indicators of a company's economic health (Mishra & Misra, 2019; Quesado et al., 2018). Non-financial measures, including customer satisfaction, employee engagement, and operational efficiency, offer insights into the firm's long-term sustainability and ability to meet its strategic objectives (Gavrea et al., 2020; Jain & Ansari, 2018). The Balanced Scorecard framework is widely used to integrate these diverse metrics, ensuring that an organization balances short-term financial goals with long-term strategic outcomes, including adaptability to market changes and maintaining customer loyalty (Kaplan & Norton, 2020). In the insurance industry, specific metrics like claim processing times, customer retention rates, and compliance with regulatory standards are critical in determining a firm's performance and competitiveness (Hussain et al., 2018; Kalyani, 2019).

This study will use efficiency and customer satisfaction as key measures of performance. Efficiency, often operationalized through metrics like the expense ratio and claim processing times, reflects how well an insurance company manages its resources to deliver services at a minimal cost while maximizing output (Albrecht et al., 2019). High efficiency indicates streamlined operations and cost-effective service delivery, which are crucial in maintaining profitability and competitiveness (Ikram et al., 2020). Customer satisfaction, on the other hand, measures the extent to which insurance services meet or exceed customer expectations, making it a critical non-financial indicator that influences customer loyalty, retention rates, and overall market share (Wang et al., 2021). The insurance sector in Kenya has faced significant challenges in efficiency and customer satisfaction, as evidenced by recent statistics. According to a 2023 report by the Insurance Regulatory Authority (IRA), customer satisfaction in the sector dropped to 58%, down from 63% in 2022, largely due to delays in claim processing and poor customer service (IRA, 2023).

Additionally, the sector's efficiency ratings have been concerning, with an average claim settlement period of 90 days, compared to the global benchmark of 30 days, leading to increased customer dissatisfaction (Association of Kenya Insurers, 2023). The industry's overall Net Promoter Score (NPS) stood at a low of -10, indicating that more customers are likely to discourage others from engaging with insurance firms than to recommend them (PwC Kenya, 2023). These trends highlight a critical need for the adoption of technologies like AI to improve operational efficiency and enhance customer experience. By focusing on these two metrics, the study aims to capture a comprehensive view of how well insurance firms in Kenya perform in both operational and customer-centric aspects, which are essential for long-term success in the industry.

2.4 Artificial Intelligence and Organizational Performance

Pradeep and Patil (2022), Dutt (2020), and Kelley et al. (2018) collectively emphasize the transformative potential of AI in the insurance sector, particularly in enhancing decision-making and operational efficiencies. Pradeep and Patil (2022) highlight AI's ability to improve customer response mechanisms and streamline operations within global insurance firms, though they acknowledge some ethical concerns. Similarly, Dutt (2020) focuses on AI’s role in health insurance, where it enhances risk assessment, fraud prevention, and customer service, even if the study overlooks the regulatory complexities involved. Kelley et al. (2018) extend this discussion by predicting significant shifts in the insurance value chain due to AI, particularly through improved data analytics and underwriting capabilities. However, all three studies, despite their optimistic outlook on AI, recognize the need to address challenges such as ethical considerations, regulatory hurdles, and the socio-economic implications of AI adoption.

Contrasting these views, Śmietanka et al. (2020), Moyo et al. (2022), and Area (2023) present a more critical perspective on AI's integration into the insurance industry, focusing on the operational challenges and limitations. Śmietanka et al. (2020) acknowledge the computational strengths of AI in automating operations and advancing risk analysis but caution that integrating these systems into existing infrastructures poses significant challenges. Moyo et al. (2022), using the TOE model, identify resource constraints, skill shortages, and high costs as key barriers to AI adoption in Zimbabwe's insurance sector, emphasizing the need for tailored regulatory frameworks. Area (2023) introduces the AI-Based Risk Intelligence Model (RIM) for underwriting, noting its potential in optimizing risk management but also pointing out the lack of empirical validation and the challenges of real-world implementation. These studies collectively suggest that while AI holds promise, its successful integration into the insurance sector requires a nuanced approach that considers practical, operational, and contextual factors.

Regionally focused studies by Ndlovu et al. (2023), Okoye and Ibrahim (2022), and Silva and Costa (2021) further demonstrate how AI is being applied in specific insurance markets, each highlighting different benefits and challenges. Ndlovu et al. (2023) explore AI's impact on claims processing efficiency in South Africa, noting significant reductions in processing times and improved accuracy, which have enhanced customer satisfaction and operational agility. In Nigeria, Okoye and Ibrahim (2022) examine the use of AI-driven chatbots in customer service, showing how these tools have revolutionized customer interactions and improved service efficiency, positioning insurers to meet evolving market demands. Meanwhile, Silva and Costa (2021) explore AI's role in refining risk assessment models in Brazil, where AI-powered algorithms have led to more accurate risk predictions and optimized underwriting processes. Together, these studies illustrate the regional adaptability of AI, although they also highlight the unique challenges and opportunities that arise in different contexts.

Building on these regional insights, Muturi and Mwangi (2020), Martinez and Gomez (2023), and Silva and Costa (2021) underscore AI's impact on fraud detection, pricing, and market competitiveness within insurance. Muturi and Mwangi (2020) demonstrate that AI algorithms significantly enhance fraud detection accuracy in Kenya, reducing financial losses and strengthening regulatory compliance. Martinez and Gomez (2023) reveal that in Argentina, AI-driven pricing models allow insurers to offer personalized premiums based on real-time data, which improves customer satisfaction and enhances market competitiveness. Silva and Costa (2021) further show how Brazilian insurers leverage AI to optimize pricing structures, attract a broader customer base, and increase profitability. Collectively, these studies highlight how AI is reshaping key aspects of the insurance industry, driving innovation in fraud prevention, pricing strategies, and competitive positioning across different markets.

The studies frequently employ AI models like predictive analytics, machine learning (ML), and deep learning (DL) to enhance various insurance operations. Predictive analytics, as used by Area (2023) and Martinez and Gomez (2023), helps in forecasting risks and personalizing insurance premiums by analyzing patterns in large datasets. Machine learning, seen in studies like those by Pradeep and Patil (2022) and Muturi and Mwangi (2020), is applied to tasks such as fraud detection and risk assessment, where it identifies trends and anomalies that might indicate fraudulent activities. Deep learning, mentioned by Śmietanka et al. (2020), is utilized for more complex analysis, such as refining underwriting processes, due to its ability to process vast amounts of data and improve accuracy over time. This study will adopt predictive analytics in determining the relationship that exists between the research variables.

2.5 Insurance sector in Kenya

The insurance sector in Kenya plays a significant role in the country's economy by offering financial protection against risks and uncertainties. Defined as a mechanism for transferring risk from individuals or entities to an insurer in exchange for a premium, insurance in Kenya has evolved to cater to a wide range of industries and consumer needs. The sector encompasses life insurance, which provides coverage for death, disability, and related benefits, and non-life insurance, which covers health, property, and liability risks (Ogutu, 2019; Waweru & Kisaka, 2021). With the Kenyan economy experiencing steady growth, the demand for insurance services has surged as both individuals and businesses seek to safeguard their investments and assets (Mwangi et al., 2020). Additionally, the regulatory framework under the Insurance Regulatory Authority (IRA) ensures that the industry adheres to ethical standards and operates efficiently, thereby fostering trust among policyholders.

Operationalization within the Kenyan insurance sector entails the implementation of policies and strategies that cater to the dynamic needs of the market. Insurance firms have adopted digital solutions to enhance customer experience, streamline operations, and improve service delivery (Maina, 2020; Muthoni & Mwangi, 2019). For instance, the integration of mobile technology has revolutionized insurance access by enabling policyholders to buy, renew, and claim insurance through mobile platforms, reducing traditional barriers such as geographical limitations (Owino & Nyaga, 2020). Companies like Britam and Jubilee Insurance have invested in innovative products like micro-insurance, targeting low-income earners who require affordable and accessible insurance coverage (Chepkoech, 2020). Through these developments, insurance firms have expanded their market reach, contributing to the growth of the sector. Moreover, operationalization involves ensuring compliance with regulatory requirements and managing risks effectively, which are critical for sustaining the industry's long-term viability.

The composition of the Kenyan insurance industry is characterized by both local and international players, with 56 licensed insurance companies, several insurance brokers, and numerous insurance agents (IRA, 2022; Otieno, 2019). Major players such as UAP Old Mutual, CIC Insurance, and APA Insurance dominate the market, offering a diverse range of products from health insurance to motor vehicle and agricultural insurance (Mugambi, 2019). The presence of multinational insurance firms like Allianz and AIG underscores the attractiveness of the Kenyan market, driven by an expanding middle class and growing business environment (Njenga & Kiragu, 2021). These companies leverage global best practices while adapting to local needs, resulting in a competitive landscape. Furthermore, the insurance distribution channels in Kenya include direct sales, bancassurance, and online platforms, with bancassurance—insurance sold through bank channels—gaining popularity as a convenient and efficient method (Kiplangat, 2019). The industry also benefits from professional bodies like the Association of Kenya Insurers (AKI), which plays a pivotal role in promoting industry standards and advocating for favorable policies.

Despite these advancements, the Kenyan insurance sector faces several challenges that hinder its growth potential. Issues such as low penetration rates, estimated at around 3% of the GDP, highlight the need for more awareness and education on the importance of insurance among the general population (Muturi, 2021; Gichuki et al., 2020). Cultural factors, mistrust, and the perception that insurance is a service for the elite further exacerbate these challenges, leading to a slow uptake of insurance products in rural areas (Kimani, 2018). In response, insurers have rolled out public education campaigns and simplified insurance policies to demystify insurance and attract more customers (Gichure, 2019). Additionally, the IRA has introduced measures to ensure financial soundness within the sector, including strict solvency requirements and regular audits to mitigate risks associated with undercapitalized firms (Karanja & Muturi, 2020). These efforts are geared towards enhancing consumer confidence and ensuring the stability of the insurance market.

Furthermore, the insurance sector in Kenya is increasingly focusing on product diversification to meet the needs of different market segments. Insurance companies are developing specialized products such as takaful (Islamic insurance), crop insurance, and health insurance tailored to unique customer requirements (Mutiso, 2020; Odhiambo & Owino, 2021). The introduction of takaful insurance, for instance, aligns with the religious beliefs of the Muslim population, thereby broadening market reach (Kinyanjui & Njiru, 2020). Similarly, agricultural insurance products have gained traction as they provide farmers with financial protection against adverse weather conditions, pests, and diseases, which are prevalent in Kenya's largely agrarian economy (Nyangweso et al., 2020). Health insurance schemes, including government-backed initiatives like the National Hospital Insurance Fund (NHIF), have also expanded to cover a larger portion of the population, especially with recent reforms aimed at universal health coverage (Wafula & Wanjiru, 2020). This diversification strategy not only addresses the evolving needs of consumers but also enhances financial inclusion and resilience among vulnerable groups.

The regulatory landscape governing the insurance sector in Kenya is integral to its development and sustainability. The Insurance Regulatory Authority (IRA), established under the Insurance Act, Cap 487, is tasked with regulating, supervising, and developing the industry (Waweru & Kairu, 2020; Makori & Omondi, 2019). The IRA enforces compliance with legal provisions, oversees the solvency of insurance firms, and ensures that the interests of policyholders are protected. In addition to the IRA, the government has enacted various policies aimed at stimulating growth within the sector, including tax incentives for insurers and the promotion of public-private partnerships (PPPs) in insurance schemes (Njiru & Mwangi, 2021). The introduction of risk-based capital requirements is another significant regulatory reform that has enhanced the financial stability of insurance firms by ensuring they hold adequate capital relative to the risks they underwrite (Kamau, 2020). These regulatory frameworks contribute to the overall credibility of the sector and foster an environment conducive to innovation and competition.

2.6 Conceptual framework

Conceptual framework was used to illustrate the relationship between the research variables (Mugenda & Mugenda, 2008). Figure 2.1 shows the conceptual framework which was adopted by the study.

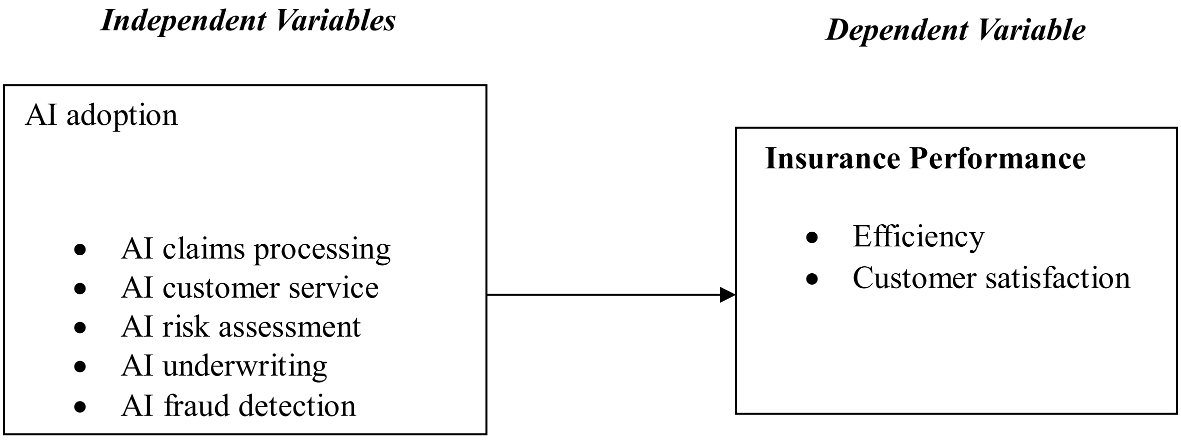

Figure 2. 1:Conceptual Framework

Source: Researcher (2024)

2.7 Research Gaps

From the reviewed literature, it is evident that while AI holds immense promise for revolutionizing the insurance industry through enhanced efficiencies and data-driven insights, its adoption faces significant challenges. These include regulatory hurdles, ethical considerations, and socio-economic Effects that necessitate nuanced research and collaborative policy frameworks to maximize AI's potential while mitigating risks across diverse global insurance landscapes.Table 2.1 presents a summary of the reviewed literature and emmerging research gaps.

Table 2. 1: Summary of Literature and Research Gaps

Author (Year)	Focus of the Studies	Findings	Research Gaps	Focus of the current study
Pradeep and Patil (2022)	AI's application in addressing customer dissatisfaction and organizational	Highlights AI's potential to enhance customer response mechanisms and operational efficiencies. Lacks addressing ethical implications, biases in AI algorithms,	Ethical implications, biases in AI algorithms, implications for smaller firms,	Kenyan insurers might face similar challenges regarding AI's ethical use, integration feasibility for smaller firms, and compliance with local regulations.

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	challenges in global insurance firms.	practical implications for smaller firms, and regulatory challenges.	regulatory challenges.	
Śmietanka et al. (2020)	Review of data science technologies and AI algorithms impacting insurance markets.	AI's role in automating operations, advancing risk analysis capabilities, and introducing new learning paradigms. Overlooks operational challenges of integrating AI systems and data privacy concerns.	Integration challenges, data privacy concerns.	Kenyan insurers could face challenges in integrating complex AI systems into existing infrastructures and addressing data privacy concerns, similar to those highlighted in the study.
Area (2023)	AI's influence on insurance underwriting processes through AI-Based Risk Intelligence Model (RIM).	Integrates predictive analytics and ML to optimize risk management strategies. Lacks empirical validation and real-world implementation challenges.	Empirical validation, real-world implementation challenges.	Implementing AI-based models like RIM in Kenya may encounter challenges in empirical validation across diverse contexts and ensuring sustainable adoption without robust industry-wide metrics.
Dutt (2020)	AI's role in addressing challenges in health insurance.	Benefits in risk assessment, fraud prevention, and customer service. Overlooks regulatory complexities, data security issues, and socioeconomic implications.	Regulatory complexities, data security, socioeconomic implications.	Similar regulatory and data security challenges might be faced by Kenyan insurers looking to adopt AI in sensitive domains like health insurance, impacting its potential benefits as discussed in the study.
Kelley et al. (2018)	AI's transformative impact on the insurance value chain.	Predicts enhanced data analytics and underwriting capabilities. Speculative on societal Effects and overlooks socio-political factors shaping AI integration.	Societal Effects, socio-political factors.	Kenyan insurers might need to consider socio-political factors and conduct empirical studies on AI's societal Effects, as

				seen in other contexts.
Moyo et al. (2022)	Barriers to AI and ML adoption in the Zimbabwe an insurance sector using the TOE model.	Identifies resource constraints, skill shortages, and high costs as primary obstacles. Emphasizes the need for tailored regulatory frameworks and international collaborations.	Tailored regulatory frameworks, internationa l collaboratio ns.	Similar barriers in Kenya could include resource constraints and the need for tailored regulatory frameworks to support sustainable AI adoption in the insurance sector, aligning with findings in Zimbabwe.
Ndlovu et al. (2023)	AI technologi es reshaping claims processing efficiency in the South African insurance industry.	Significant reductions in processing times, improved accuracy in claim assessments. Emphasizes AI's role in transforming traditional processes.	Transformat ion of traditional processes.	Kenyan insurers could benefit similarly from AI technologies to enhance claims processing efficiency and operational agility, akin to advancements seen in South Africa.
Okoye and Ibrahim (2022)	Integratio n of AI-driven chatbots in customer service within the Nigerian insurance sector.	Revolutionizes customer interactions, reduces response times, and increases service availability.	Enhanced customer service, automation of routine queries.	Similar adoption of AI-driven solutions in Kenya could enhance customer service and operational efficiency, as observed in the Nigerian context.
Silva and Costa (2021)	AI's impact on risk assessmen t models in Brazilian insurance companies .	AI-powered algorithms analyze datasets comprehensively, leading to more accurate risk predictions. Enhances underwriting processes and profitability.	Underwritin g process enhancemen t, profitability.	Kenyan insurers could explore AI's potential in refining risk assessment models and improving profitability, similar to Brazilian practices.
Muturi and	AI's role in fraud detection	AI algorithms detect fraudulent claims accurately, reducing	Fraud detection accuracy,	Kenyan insurers can leverage AI for fraud detection to enhance

Mwangi (2020)	within the Kenyan insurance sector.	financial losses and enhancing trust and compliance efforts.	trust enhancement.	financial stability and regulatory compliance, as shown in local studies.
Martinez and Gomez (2023)	Use of AI in insurance pricing strategies in Argentina.	AI-driven pricing models analyze customer data in real-time, offering personalized premiums and enhancing competitiveness.	Real-time pricing analysis, competitiveness.	Kenyan insurers could consider AI-driven pricing strategies to offer personalized premiums and improve competitiveness, drawing insights from Argentinean practices.

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CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter evaluates the criteria for determining the best possible methodology for this research study. The chapter encompasses the research design, study population and sample, reliability and validity, data analysis and finally the ethical considerations.

3.2 Research design

The study employed a mixed research design, integrating both descriptive and exploratory approaches. The descriptive research design was used to address the first research objective, as it allows for the collection, summarization, and interpretation of data to provide an accurate profile of AI adoption in insurance companies. Descriptive research enables researchers to outline conditions, events, and behaviors systematically, making it suitable for determining the extent of AI adoption. Meanwhile, the exploratory research design was applied to the second objective, as it seeks to examine the effect of AI adoption on insurance company performance. Given that the impact of AI on customer satisfaction and efficiency involves investigating relationships and underlying patterns, an exploratory approach was necessary to gain deeper insights into these effects. This combination of research designs ensured a comprehensive understanding of AI adoption and its implications in the insurance sector (Creswell & Creswell, 2017).

3.3 Population

Population of the study refers to the complete set of individuals, objects, or events that possess common characteristics and are of interest to a researcher for a specific study. It represents the total group from which a researcher aims to draw conclusions or make inferences, (Creswell 2014). The study population is the whole group of people. According to Mugenda and Mugenda (2019), population is the entire group of individuals, actions, or stuff with similar characters. The unit of analysis was 23 general insurance companies and the unit of observation was 138 employees from the following departments: claims processing, customer service, underwriting, risk management and IT and innovations.

3.4 Data Collection Instruments

The main data collection instrument for this study was questionnaire. This was developed through the guidance of the objectives and research questions. The questionnaire contained close-ended questions to allow the respondents give their opinion concerning the study. The questionnaires were issued, filled and collected after two weeks to ensure validity of the research instrument, the research questions were made precise and were based on the objectives of the study. A stratified random sampling approach was used to ensure that responses were balanced across departments, including claims processing, underwriting, customer service, IT, and risk management. This minimized selection bias and provided a comprehensive view of AI adoption across different functions in insurance firms.

3.5 Pilot Study

The drive of a pilot test is to identify possible weaknesses, inadequacies and constraints in all aspect of the research process. A pilot study will be conducted among 14 participants from 3 insurance companies in Kiambu County including Britam Holdings PLC, Jubilee Holdings Limited, and CIC Insurance Group. This consisted of approximately 10% of the target population, (Kothari 2012). The piloted questionnaires were not included in the main study.

3.5.1 Validity of the Instrument

Validity is the level to which outcomes obtained from the data investigation essentially denote the phenomenon under investigation (Schonhaut et al., 2013). In this study, content validity will be tested to ensure that each measurement item adequately reflects the concept being examined. Content validity emphasizes the relevance and representativeness of the research instruments before any theoretical interpretations are made (Golafshani, 2013). This process involved examining the questions or indicators used in the study comprehensively capture the intended variables, ensuring that the data collected is both meaningful and appropriate for analysis.

3.5.2 Reliability of the Instrument

To enhance the reliability of the instrument, the researcher will apply multiple strategies in addition to consulting with the supervisor. A pilot study will be conducted among 14 participants from 3 insurance companies in Kiambu County. Cronbach's Alpha (α) will be used to determine internal consistency, which is essential for establishing reliability. Cronbach's Alpha is a statistical measure that evaluates how closely related a set of items are as a group. In this study, an alpha value of 0.7 or higher will be considered acceptable, indicating that the instrument had a reliable level of internal consistency for measuring each independent variable.

3.6 Data Collection Procedures

Before commencement of the study, the researcher sought consent from the administration of respective targeted companies. The researcher hand-delivered the questionnaires to the respective Saccos, and made follow-up periodically through phone calls and emails to ensure a good response. Data was collected with the aid of research assistants since the study was in a large area of Nairobi County.

3.7 Measurement of Study Variables

Table 3.1 shows measurement of the variables of the study.

Table 3. 1: Measurement of Study Variables

Variable	Measure	Scale
Insurance Performance	-Customer satisfaction score for AI-handled services - Number of claims processed per day due to AI	-Continuous (claims/day) -Ordinal (1-5 scale)
AI Claims Processing	Proportion of total claims processed using AI	Ratio (0-1)
AI Customer Service	Average response time of AI in customer service interactions	Continuous (seconds)
AI Risk Assessment	Rate of premium adjustments based on AI-driven risk assessments	Continuous (rate)
AI Underwriting	Percentage of underwriting errors reduced due to AI implementation	Ratio (0-1)

3.8 Data Analysis and Presentation

To prepare the data collected by the study for analysis, the data was checked for completeness, coded and data entry is done. Quantitative data was analyzed statistically after being entered into R. This software facilitated efficient and accurate processing of the data. The analysis employed a cohesive set of statistical techniques including descriptive statistics to summarize AI adoption levels, Pearson correlation analysis to examine relationships between AI adoption and efficiency/customer satisfaction, and regression models to predict the effect of AI-driven processes on claims processing speed and fraud detection rates. The regression model was as below.

$Yit = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_3 t + \beta_4 X_{4t} + \varepsilon$

Where:

Y_{it} represents the dependent variable for Insurance Performance i at time t.

X_{1t} represents the AI Claims Processing at time t.

X_{2t} represents the AI Customer Service at time t.

X_{3t} represents the AI Risk Assessment at time t.

X_{4t} represents the AI Underwriting at time t.

ε is the error term.

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CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

4.1 Response Rate

The study issued 138 questionnaires to employees from 23 selected insurance companies within Nairobi. Out of which 115 were successfully filled and returned. This represented 83% response rate. However, 17% response rate was not received because the 23 questions were not correctly filled by the employees. According to Draugalis (2018) a response rate of a response rate of 70% or higher is generally considered excellent. Response rates in the range of 50% to 69% are often considered good, and researchers may still be able to draw meaningful conclusions from the data. Response rates below 50% are generally considered low, and researchers need to be especially vigilant about nonresponse bias. Therefore, the response rate of 83% was highly acceptable.

Table 4. 1: Response Rate

Sampled No. of Respondents	No. of Questionnaires Returned	Response Rate (%)
138	**115**	**83%**

Source: Research Data (2025)

4.2 Demographic Information

Demographics of the respondents included, designation of the respondent, department of the respondents, number of employees in the organization and level of ai integration in the organization's operation as indicated here in.

4.2.1 Designation of the Respondent

The researcher sought to assess the designation of the respondent; the findings were as indicated in Figure 4.1

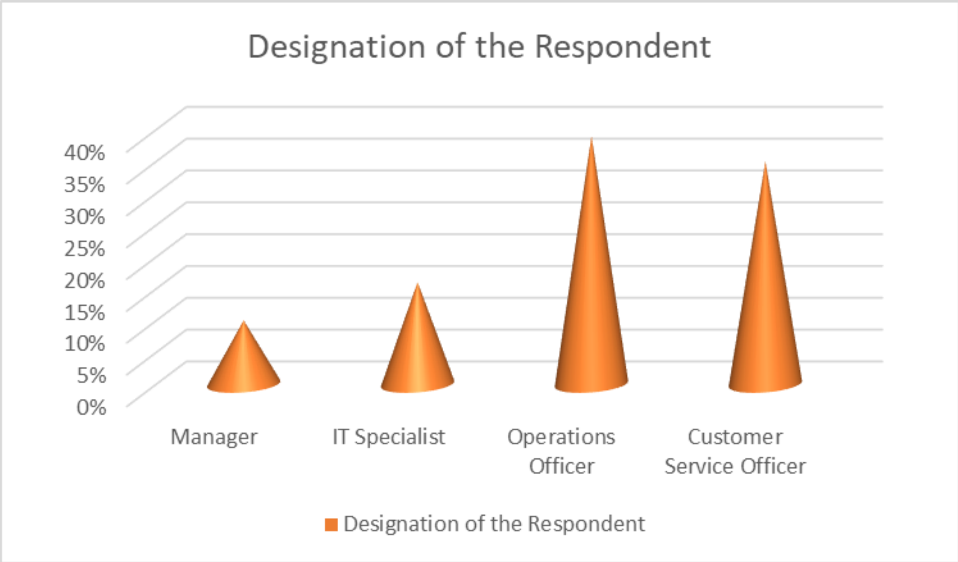

Figure 4. 1: Designation of the Respondent

Source: Research Data (2025)

From the analysis in figure 4.1, the study revealed that 12 (10%) of the respondents were managers, 18 (16%) were IT specialists, 45 (39%) were operations officers, and 40 (35%) were customer service officers. This implies that the roles of operations officers and customer service officers comprised the largest portion of respondents. These positions are likely more involved in direct interactions with AI technologies, such as AI claims processing and AI-powered customer service tools like chatbots. The fact that a smaller number of respondents were managers and IT specialists indicates that while these roles are critical for decision-making and implementing AI, they represent a smaller proportion of the workforce in the sample. This may suggest that the majority of employees engaging directly with AI systems are those in operational roles.

4.2.2 Department of the Respondents

The researcher also sought to assess the department of the respondents, the findings were as indicated in table, 4.3.

Table 4. 2: Department of the Respondents

Department	Frequency	Percentage
Claims Processing	30	26
Customer Service	32	28
Underwriting	20	17
Risk Management	15	13
IT and Innovations	18	16
Total	115	100

Source: Research Data (2025)

In Table 4.3, the study showed that 30 (26%) respondents were from Claims Processing, customer service had 32 (28%) of the respondents, underwriting department had 20 (17%) of the respondents, risk management had 15 (13%) of respondents. Finally, 18 (16%) of the respondents were from IT and Innovations. This department plays a crucial role in implementing and overseeing AI systems, but its smaller share of the sample suggests that IT and Innovations departments may be relatively less populated than other departments, reflecting the specialized nature of these roles. Claims processing is a key area where AI can improve efficiency and accuracy, particularly using automation in claims handling. The significant proportion of respondents from this department suggests that AI adoption is most noticeable in claims processing functions. AI in risk management typically involves predictive analytics for better forecasting of risks and managing claims.

4.2.3 Number of Employees in Your Organization

The researcher also sought to assess the number of employees in the organization, the findings were as indicated in Figure 4.2

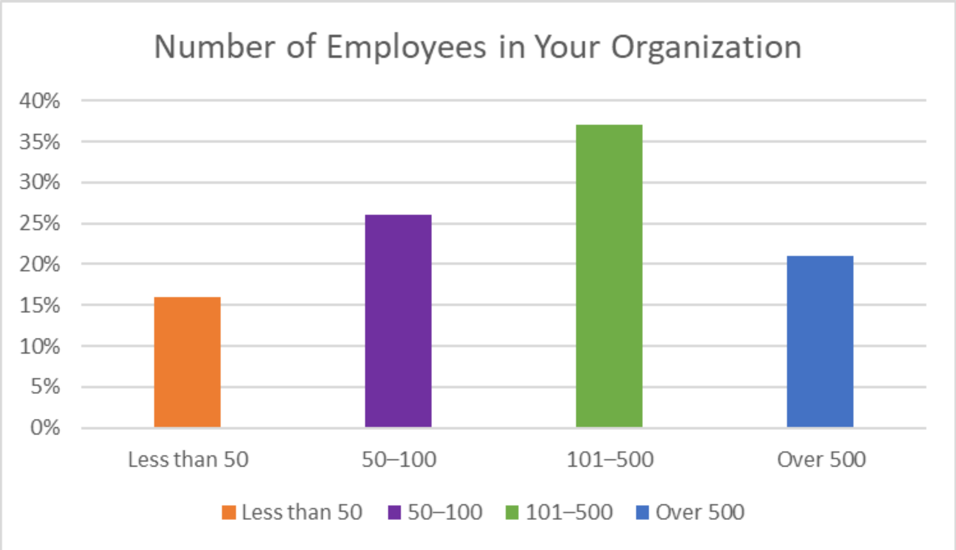

Figure 4. 2: Number of Employees in Your Organization

Source: Research Data (2025)

From the data in figure 4.2, the study found that 18 (16%) of the insurance companies had Less than 50 employees, 30 (26%) of the insurance companies had, 50-100 employees, 40(37%) had 10-500 employees, 25(21%) had over 500 employees. This implies that majority of the respondents had 100-500 employees.

4.2.4 Level of AI Integration in the Organization's Operations

The researcher sought to assess the level of AI integration in the organization's operations, the findings were as indicated in Figure 4.3

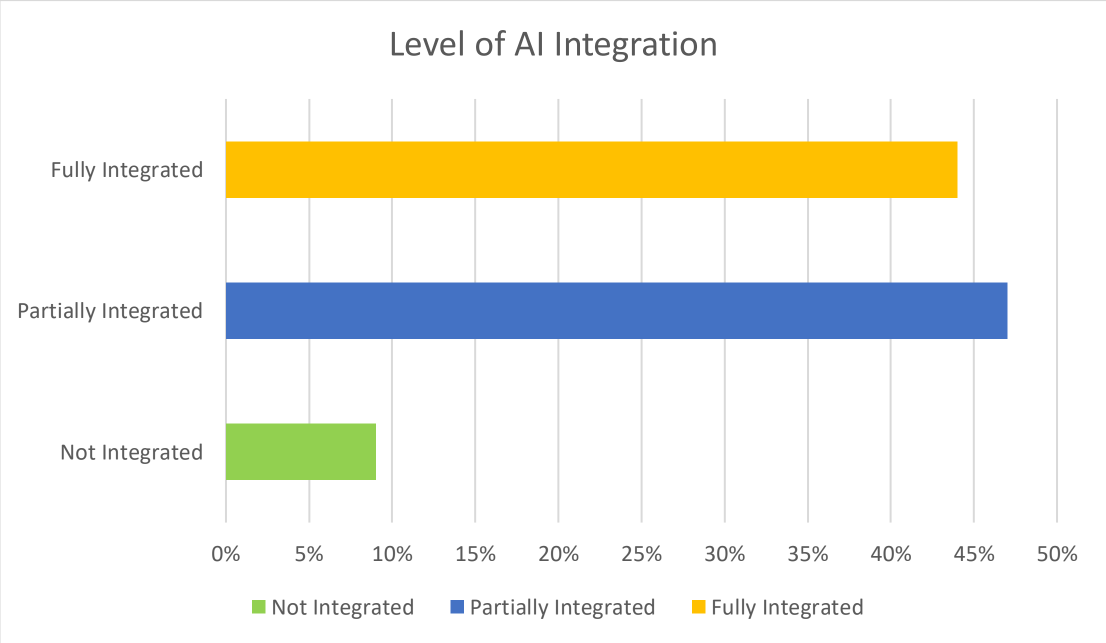

Figure 4. 3: Level of AI Integration in the Organization's Operations

Source: Research Data (2025)

As presented in figure 4.3, the study found that 10 (9%) of the respondents reported that AI was not integrated into their organizations, 54 (47%) of the respondents, reported that AI was partially integrated into their organization's operations, 51 (44%) of the respondents indicated that stated that AI was fully integrated into their organization's operations. This implies that in most insurance companies, AI was partially integrated. This finding suggests that many organizations are in the process of adopting AI technologies but have not yet fully integrated them across all departments. This phase could involve the initial use of AI tools for specific functions, such as chatbots for customer service or basic AI-driven risk assessment tools.

4.3 Adoption of AI technology

4.3.1 Extent to which the Insurance Company has Adopted AI Technology

The study asked the respondents to indicate the rate at which the organization has adopted the following AI technologies as indicated in table 4.3.

Table 4. 3: Extent to which the Insurance Company has Adopted AI Technology

AI Technology	Not Adopted		Low Extent		Moderate Extent		High Extent		Very High Extent		Mean	Standard Deviation
	F	**%**	**F**	**%**	**F**	**%**	**F**	**%**	**F**	**%**	**($\bar{x}$)**	**(σ)**
AI Claims Processing	12	10%	18	16%	35	30%	28	24%	22	19%	3.26	1.23
AI Customer Service (Chatbots)	10	9%	20	17%	32	28%	40	35%	13	11%	3.23	1.13
AI Risk Assessment	15	13%	22	19%	28	24%	30	26%	20	17%	3.16	1.28
AI Underwriting	8	7%	25	22%	34	30%	30	26%	18	16%	3.22	1.16
AI Fraud Detection	14	12%	18	16%	30	26%	33	29%	20	17%	3.23	1.25

Source: Research Data (2025)

According to the findings from Table 4.3, a significant portion of respondents indicated that AI claims processing is utilized to a moderate extent (30%), while a smaller percentage reported a high (24%) and very high extent (19%), resulting in a mean score of 3.26 and a standard deviation of 1.23. However, a notable proportion of the respondents still perceive adoption as low (16%) or not adopted (10%), indicating room for further improvement. Similarly, AI customer service, particularly through chatbots, has gained traction but remains at a moderate level, with 28% of respondents acknowledging its moderate usage and a slightly higher percentage (35%) indicating high adoption. Nonetheless, a considerable fraction still sees adoption as low (17%) or nonexistent (9%), with a mean score of 3.23 and a standard deviation of 1.13. These findings suggest that while AI claims processing and chatbots are gaining acceptance, there remains a gap in achieving widespread adoption.

AI risk assessment, which plays a critical role in evaluating potential policyholder risks, has seen modest adoption, with a moderate extent reported by 24% of respondents. A slightly higher proportion of respondents indicated high (26%) and very high (17%) adoption, leading to a mean score of 3.16 and a standard deviation of 1.28. However, a substantial number of respondents still perceive adoption as low (19%) or entirely absent (13%), highlighting the need for further investment in AI-driven risk assessment tools. Similarly, AI underwriting, which enhances efficiency in policy evaluation, exhibits a moderate level of adoption, with 30% of respondents reporting moderate usage and an additional 26% indicating high adoption. While 16% perceive very high adoption, a considerable proportion of respondents still view adoption as low (22%) or nonexistent (7%), leading to a mean score of 3.22 and a standard deviation of 1.16. These results indicate that while AI is transforming risk assessment and underwriting, some resistance or limitations in implementation persist.

AI fraud detection has been adopted at varying degrees, with 26% of respondents indicating moderate usage, 29% reporting high adoption, and 17% perceiving very high adoption. The mean score of 3.23 and a standard deviation of 1.25 suggest that adoption is progressing but remains inconsistent. A significant proportion of respondents still believe AI fraud detection is adopted to a low extent (16%) or not at all (12%), reflecting potential barriers such as cost, integration challenges, or skepticism regarding effectiveness. The variations in adoption across AI functions highlight the uneven implementation of AI technologies within the company, with some areas seeing higher uptake than others. While AI claims processing, customer service chatbots, underwriting, and fraud detection exhibit promising adoption trends, further investment and training may be required to enhance adoption levels across all functions. The results suggest that AI is playing an increasingly vital role in insurance operations, but its full potential has yet to be realized across all domains.

4.3.2 Percentage of the Organization Driven by AI Technology

The researcher sought to assess the percentage of the organization operations driven by AI technologies. The findings were as indicated in table 4.4

Table 4. 4: Percentage of the Organization Driven by AI Technology

Percentage of AI-driven Operations	Frequency	Percentage (%)
Less than 10%	15	13
10–30%	25	22
31–50%	35	30
51–70%	25	22
More than 70%	15	13
Total	**115**	**100%**

Source: Research Data (2025)

According to the findings in Table 4.4, 13% of the respondents indicated that less than 10% of their insurance operations are driven by AI technologies. This suggests that a small proportion of organizations are still in the early stages of AI adoption, with AI being applied to only a limited number of operations. The finding aligns with those of Pradeep and Patil (2022) who observed that many organizations, especially those in traditional industries, have yet to fully integrate AI technologies into their core operations.

The study further revealed that 22% of the respondents reported that 10–30% of their operations were driven by AI technologies. This indicates a moderate level of AI adoption, with some parts of the organization benefiting from AI implementation. This aligns with the findings of Dutt (2020) who noted that many firms begin with smaller-scale AI projects before expanding their use across broader operational functions. Furthermore, 30% of respondents indicated that 31–50% of their operations were AI-driven, which indicates that a significant portion of the organization's activities are now utilizing AI technologies. This finding reflects a higher level of AI adoption, similar to the study Okoye and Ibrahim (2022), who found that AI adoption tends to increase as organizations witness the tangible benefits of enhanced decision-making and efficiency in key operations such as risk assessment and underwriting.

Additionally, 22% of the respondents reported that 51–70% of their organization's operations were AI-driven. This suggests that a considerable portion of the organization’s functions have already integrated AI technologies. This finding is consistent with the research of Muturi and Mwangi (2020), who found that organizations in highly competitive sectors, such as insurance and finance, are likely to adopt AI in a larger percentage of their operations to gain a competitive edge. Finally, 13% of respondents indicated that more than 70% of their organization's operations were driven by AI technologies. This suggests that a small but significant number of organizations have undergone substantial AI integration, with AI playing a central role in their operational processes. This is consistent with the findings of Lee and Taylor (2018), who noted that organizations that adopt AI on a large scale often see substantial improvements in productivity and efficiency, particularly in areas such as customer service, fraud detection, and risk management.

4.4 Effects of AI on Aspects of Processing

The study asked the respondents to rate the impact of AI on the following aspects of processing as indicated in table 4.5

Table 4. 5: Impact of AI on Aspects of Processing

Aspect	No Impact F %	Low Impact F %	Moderate Impact F %	High Impact F %	Very High Impact F %	Mean ($\bar{x}$)	Std Dev (σ)
AI Claims Processing	10 9%	15 13%	30 26%	40 35%	20 17%	3.39	1.17
Speed of Claims Processing	8 7%	20 17%	28 24%	42 36%	17 15%	3.35	1.13
Accuracy in Claims Handling	12 10%	18 16%	35 30%	30 26%	20 17%	3.24	1.21
AI Customer Service	14 12%	22 19%	32 28%	30 26%	17 15%	3.12	1.23
Timeliness in Responding to Queries	10 9%	18 16%	30 26%	37 32%	20 17%	3.34	1.21
Personalized Interaction	12 10%	25 22%	30 26%	35 30%	13 11%	3.10	1.17
AI Risk Assessment	8 7%	18 16%	33 29%	34 30%	22 19%	3.38	1.16
Ability to Predict Risk Accurately	10 9%	20 17%	28 24%	35 30%	22 19%	3.34	1.22
Speed of Risk Assessment	12 10%	15 13%	30 26%	38 33%	20 17%	3.34	1.21
AI Underwriting	14 12%	20 17%	28 24%	30 26%	23 20%	3.24	1.29

Efficiency in Policy Creation	12 10%	22 19%	30 26%	32 28%	19 17%	3.21	1.23
Reduction in Underwriting Errors	15 13%	18 16%	35 30%	30 26%	17 15%	3.14	1.23
AI Fraud Detection	10 9%	25 22%	30 26%	35 30%	15 13%	3.17	1.17
Speed of Detecting Fraudulent Claims	12 10%	20 17%	30 26%	35 30%	18 16%	3.23	1.21
Accuracy in Identifying Fraud	15 13%	18 16%	28 24%	34 30%	20 17%	3.23	1.27

Source: Research Data (2025)

The effect of AI on claims processing has been substantial, with a significant proportion of respondents indicating a high (35%) or very high impact (17%), leading to a mean score of 3.39 and a standard deviation of 1.17 as shown above. AI has also influenced the speed of claims processing, as evidenced by 36% of respondents reporting a high impact and 15% perceiving a very high impact, resulting in a mean score of 3.35 and a standard deviation of 1.13. However, a notable fraction of respondents still indicated that AI has had only a moderate (24%), low (17%), or no impact (7%), suggesting room for improvement in automation and efficiency. Similarly, AI has contributed to accuracy in claims handling, with a moderate (30%), high (26%), and very high impact (17%) observed, leading to a mean of 3.24 and a standard deviation of 1.21. Despite these positive effects, 16% of respondents perceived a low impact, while 10% saw no impact, highlighting potential skepticism or limitations in AI-driven claims accuracy.

AI's impact on customer service has been relatively moderate, with 28% of respondents reporting a moderate impact, 26% indicating a high impact, and 15% perceiving a very high impact, resulting in a mean score of 3.12 and a standard deviation of 1.23. However, a significant portion of respondents still reported a low (19%) or no impact (12%), suggesting that AI-based customer service, such as chatbots, may not yet fully meet user expectations. The ability of AI to enhance timeliness in responding to queries has been more pronounced, with 32% of respondents recognizing a high impact and 17% seeing a very high impact, leading to a mean of 3.34 and a standard deviation of 1.21. However, 16% of respondents still saw a low impact, while 9% perceived no impact, indicating that AI-driven response systems may require further optimization. Personalized interaction through AI remains an area of concern, with only 30% of respondents identifying a high impact and 11% seeing a very high impact, leading to a mean of 3.10 and a standard deviation of 1.17. With 22% perceiving a low impact and 10% seeing no impact, these findings suggest that AI systems may still lack the capability to provide highly tailored customer experiences.

The application of AI in risk assessment has demonstrated considerable effectiveness, with a high impact reported by 30% of respondents and a very high impact observed by 19%, leading to a mean score of 3.38 and a standard deviation of 1.16. However, a portion of respondents still indicated a moderate (29%), low (16%), or no impact (7%), suggesting that AI risk assessment tools may not yet be fully optimized or trusted. AI's ability to predict risks accurately has shown similar trends, with 30% of respondents recognizing a high impact and 19% seeing a very high impact, leading to a mean of 3.34 and a standard deviation of 1.22. Nonetheless, 24% perceived a moderate impact, 17% a low impact, and 9% no impact, reflecting varied experiences with AI-driven risk prediction models. The speed of risk assessment has also been positively influenced, with 33% of respondents reporting a high impact and 17% a very high impact, resulting in a mean score of 3.34 and a standard deviation of 1.21. However, 26% perceived only a moderate impact, 13% a low impact, and 10% no impact, pointing to inconsistencies in AI's efficiency in risk assessment processes.

AI's role in underwriting has shown promising results, with a high impact reported by 26% of respondents and a very high impact observed by 20%, leading to a mean score of 3.24 and a standard deviation of 1.29. However, a considerable proportion still perceived only a moderate impact (24%), a low impact (17%), or no impact (12%), highlighting the need for further enhancements in AI-driven underwriting processes. Efficiency in policy creation has been positively influenced, with 28% of respondents recognizing a high impact and 17% seeing a very high impact, resulting in a mean of 3.21 and a standard deviation of 1.23. Nonetheless, 26% perceived a moderate impact, 19% a low impact, and 10% no impact, suggesting that while AI is improving underwriting efficiency, its effectiveness is still evolving. AI's role in reducing underwriting errors remains moderate, with 30% of respondents identifying a moderate impact, 26% a high impact, and 15% a very high impact, leading to a mean of 3.14 and a standard deviation of 1.23. However, 16% saw a low impact, while 13% perceived no impact, indicating that underwriting errors remain a challenge despite AI implementation.

Fraud detection through AI has had a varied impact, with 30% of respondents reporting a high impact and 13% a very high impact, leading to a mean score of 3.17 and a standard deviation of 1.17. However, a notable proportion still perceived only a moderate impact (26%), a low impact (22%), or no impact (9%), suggesting that AI fraud detection systems may not yet be fully optimized or trusted. AI has also played a role in speeding up fraud detection, with 30% of respondents acknowledging a high impact and 16% seeing a very high impact, resulting in a mean of 3.23 and a standard deviation of 1.21. However, 26% reported a moderate impact, 17% a low impact, and 10% no impact, reflecting variations in AI's effectiveness. Similarly, AI's accuracy in identifying fraudulent claims has been moderately effective, with 30% of respondents recognizing a high impact and 17% a very high impact, leading to a mean score of 3.23 and a standard deviation of 1.27. However, 24% perceived a moderate impact, 16% a low impact, and 13% no impact, indicating that while AI has improved fraud detection accuracy, challenges remain in fully leveraging its potential.

4.5 Effects of AI Adoption on Customer Satisfaction

The researcher sought to assess the overall customer feedback on AI-driven services in insurance companies, as indicated table 4.6

Table 4. 6: Extent to which AI adoption has influenced Aspects of Customer Satisfaction

Customer Feedback	Frequency	Percentage (%)
Negative	10	9%
Neutral	20	17%
Positive	45	39%
Very Positive	40	35%
Total	**115**	**100%**

Source: Research Data (2025)

According to the findings in Table 4.6, the study revealed that 9% of respondents had a negative perception of AI adoption in their organization's customer satisfaction processes, while 17% expressed a neutral stance. A larger proportion, 39%, viewed the impact positively, and 35% reported that AI adoption had a very positive influence on customer satisfaction. This implies that AI-driven services in the insurance sector have largely been received favorably, with a significant portion of respondents indicating either a positive or very positive perception of the technology's impact. The results are consistent with studies such as those by Mwai and Kihoro (2019), who highlighted the beneficial impact of AI-powered chatbots and automated claims processing on customer satisfaction in African insurance companies, as they enhance service efficiency and reduce human error.

Table 4. 7: AI adoption has Influenced the Following Aspect of Customer Satisfaction

Aspect of Customer Satisfaction	Not at All		Slightly		Moderately		Greatly		Very Greatly		Mean	Std Dev
	F	**%**	**F**	**%**	**F**	**%**	**F**	**%**	**F**	**%**	**(x̄)**	**(σ)**
Responsiveness to customer inquiries	10	9%	18	16%	30	26%	35	30%	22	19%	3.36	1.20
Accessibility of customer service	12	10%	20	17%	28	24%	32	28%	23	20%	3.30	1.26
Accuracy of policy recommendations	15	13%	22	19%	25	22%	33	29%	20	17%	3.18	1.29
Reduced resolution time for claims	8	7%	18	16%	30	26%	40	35%	19	17%	3.38	1.14
Personalized customer experience	10	9%	25	22%	27	23%	30	26%	23	20%	3.27	1.25

Source: Research Data (2025)

As per Table 4.7, AI adoption has significantly influenced customer satisfaction by improving responsiveness to customer inquiries. A substantial proportion of respondents (30%) indicated that AI has greatly enhanced responsiveness, while (19%) stated it has had a very great impact, leading to a mean score of (3.36) with a standard deviation of (1.20). Similarly, accessibility of customer service has benefited from AI, with (28%) of respondents noting a great improvement, and (20%) observing a very great improvement, resulting in a mean of (3.30) and a standard deviation of (1.26). Accuracy in policy recommendations has also been positively affected, with (29%) of respondents acknowledging a great impact and (17%) indicating a very great impact, yielding a mean score of (3.18) and a standard deviation of (1.29). Additionally, AI has played a role in reducing resolution time for claims, with (35%) of respondents citing a great influence and (17%) noting a very great impact, giving a mean score of (3.38) with a standard deviation of (1.14). These statistics suggest that AI has enhanced various aspects of customer interaction, making service delivery more efficient and accessible.

Moreover, AI has contributed to a more personalized customer experience, although its impact varies. While (26%) of respondents noted a great improvement, (20%) highlighted a very great impact, leading to a mean score of (3.27) with a standard deviation of (1.25). However, a notable proportion (22%) observed only a slight influence, indicating that AI-driven personalization is yet to reach its full potential. The findings reveal that AI adoption has positively influenced different facets of customer satisfaction, but the degree of impact differs across various aspects. Some areas, such as responsiveness to inquiries and reduced claims resolution time, have shown greater advancements compared to others like policy recommendations. The variations in mean scores and standard deviations highlight the differing levels of effectiveness AI has had in transforming customer service. Overall, the integration of AI has brought meaningful improvements in customer satisfaction, but there remains room for further optimization to maximize its benefits across all service areas.

4.6. Diagnostic tests

Statistical tests were used in this research to verify if any of the assumptions wasn't met by the data.

4.6.1. Normality

Fitting data with a non-normal error term results in making wrong inferences. As such the normality of the error terms is always tested. Many tests exist in the literature, however, in this research Q-Q plot, Kolmogorov-Sminorv and Shapiro Wilk tests were used to test for normality. Q-Q plot is a scatter diagram of two quantiles. If the quantiles were from the same theoretical distribution (population) the points will form a straight line. The Q-Q plot obtained is given by figure 4.4

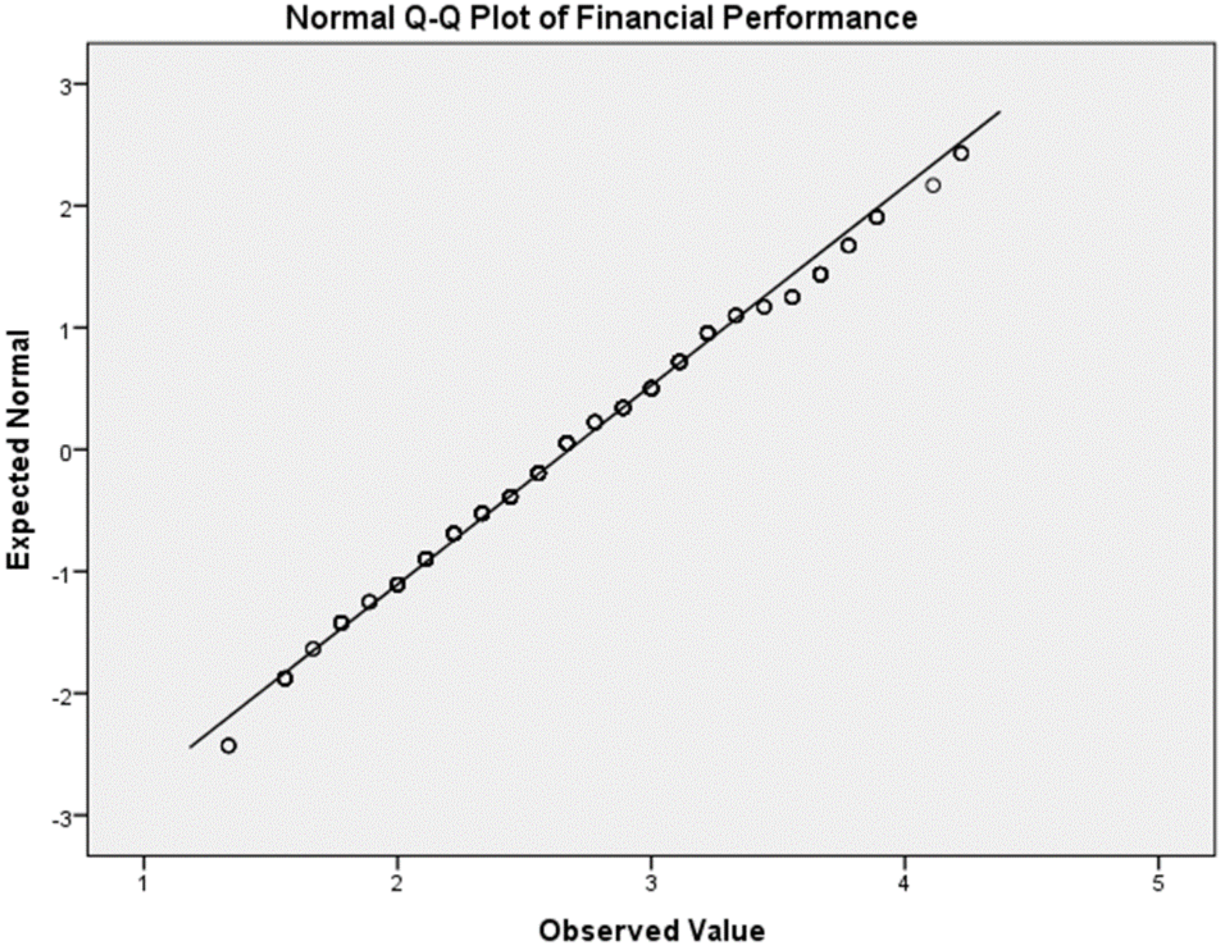

Figure 4. 4 Normal Q-Q plot

Figure 4.4 shows that the points appear to lie on a straight line hence the error terms were normally distributed. This was confirmed using the Kolmogorov-Sminorv test where the null hypothesis is that the data is normally distributed. The null hypothesis is generally rejected when the P value is less than 0.05 the specified level of significance. The result obtained is given by Table 4.5 where all the variables had p values less than 0.05.

Table 4. 8 Tests of Normality

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**Df**	**Sig.**
AI Customer Service	0.088	115	0.000	0.978	115	0.000

AI Risk Assessment	0.134	115	0.000	0.963	115	0.000
AI Underwriting	0.072	115	0.002	0.980	115	0.001
Firm size	0.082	115	0.000	0.973	115	0.000
Insurance Performance	0.079	115	0.000	0.987	115	0.020

4.6.2 Auto Correlation

Linear regression requires that the covariance (serial correlation) between the error terms should be zero. Durbin Watson test was used in this study and the results given by Table 4.9

Table 4. 9 Durbin-Watson Test

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.612[a]	0.374	0.365	0.48798	1.950

The Durbin Watson value was found to be 1.950 which is between 1.5 and 2.5 hence the model didn't suffer from auto correlation.

4.6.3 Multi collinearity

Variance Inflation Factor (VIF) was used in this research to detect for presence of multicollinearity. VIF values of more than 10 is an indication of presence of multicollinearity. The VIF results are given by Table 4.10.

Table 4. 10 VIF Test

Variables	**Collinearity Statistics**	
	Tolerance	**VIF**
AI Claims Processing	0.417	2.397
AI Customer Service	0.899	1.112
AI Risk Assessment	0.334	2.994
AI Underwriting	0.250	4.004

Table 4.10 shows that the VIF values were less than 10 hence presence of acceptable amounts of multicollinearity.

4.7. Correlation Analysis

This research used Pearson correlation coefficient to assess the strength of the relationships. Pearson correlation coefficient takes values between -1 and +1 with values close to +1 or -1 indicating a strong relationship between the two variables and values close zero indicating a weaker relationship. P values of less than 0.05 indicate presence of significant relationship and p values of more than 0.05 indicate presence of significant relationship. Table 4.11 presents the correlation matrix.

Table 4. 11 Correlation Matrix Table

		Insurance Performance	AI Claims Processing	AI Customer Service	AI Risk Assessment	AI Underwriting
Insurance Performance	Pearson Correlation	1				
	Sig. (2-tailed)					
AI Claims Processing	Pearson Correlation	.777**	1			
	Sig. (2-tailed)	0.000				
AI Customer Service	Pearson Correlation	0.356**	.130*	1		
	Sig. (2-tailed)	0.000	0.035			
AI Risk Assessment	Pearson Correlation	.551**	.636**	.306**	1	
	Sig. (2-tailed)	0.000	0.000	0.000		
AI Underwriting	Pearson Correlation	.667**	.761**	.213**	.803**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	
	Sig. (2-tailed)	0.000	0.000	0.018	0.000	0.000
	N	115	115	115	115	115

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

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

The results as shown above indicate a significant positive relationship between AI adoption and organizational performance in the insurance sector in Kenya. AI claims processing exhibited the strongest correlation with insurance performance, with a Pearson correlation coefficient of ($r = 0.777$, $p = 0.000$), indicating a highly significant relationship. This suggests that improvements in AI-driven claims processing directly enhance overall organizational performance, likely due to increased efficiency and reduced processing time. AI underwriting also demonstrated a strong positive correlation with insurance performance ($r = 0.667$, $p = 0.000$), signifying that automation in underwriting contributes to better decision-making and risk management. AI risk assessment followed closely, showing a moderate correlation with performance ($r = 0.551$, $p = 0.000$), which implies that AI-driven risk evaluation enhances firms' ability to assess and mitigate potential losses.

AI customer service had a weaker but still significant correlation with insurance performance ($r = 0.356$, $p = 0.000$), suggesting that while AI enhances customer interactions, its impact on overall performance is not as strong as claims processing or underwriting. This could be attributed to the fact that customer service improvements may not directly translate into financial performance but contribute to long-term client retention. The correlation between AI customer service and AI claims processing was low ($r = 0.130$, $p = 0.035$), though significant at the (0.05) level, indicating that these two AI functions operate somewhat independently. The relatively weaker correlation suggests that AI in customer service may require further optimization to align with performance-driven processes like claims handling. However, AI customer service still plays a role in improving the overall insurance experience, potentially fostering customer loyalty and satisfaction.

AI risk assessment showed a significant correlation with AI claims processing ($r = 0.636$, $p = 0.000$), demonstrating that risk evaluation is closely tied to the efficiency of claims management. This suggests that AI-powered risk assessment tools assist in better claims handling by identifying potential fraud or risks early in the process. Additionally, AI underwriting had the highest correlation with AI risk assessment ($r = 0.803$, $p = 0.000$), indicating that risk assessment plays a fundamental role in underwriting decisions. This relationship underscores the importance of accurate risk evaluation in creating policies that minimize insurer exposure while maximizing profitability. The strong correlation suggests that insurers that integrate AI in both underwriting and risk assessment achieve more efficient decision-making and pricing strategies.

Overall, the correlation matrix confirms that AI adoption significantly influences different facets of insurance performance, with claims processing and underwriting having the strongest impact. The significant relationships observed between AI risk assessment, underwriting, and claims processing ($p = 0.000$) indicate that AI-driven automation enhances key operational areas, leading to improved efficiency and profitability. The moderate correlation of AI customer service with insurance performance ($r = 0.356$, $p = 0.000$) suggests that while AI enhances customer interactions, its direct effect on financial performance remains limited. The presence of strong interrelationships among AI functions, such as underwriting and risk assessment ($r = 0.803$, $p = 0.000$), further highlights the interconnected role of AI-driven solutions in optimizing insurance operations.

4.8. Regression Analysis

A multiple linear regression model was fitted between the Insurance Performance and the independent variables namely AI Claims Processing, AI Customer Service, AI Risk Assessment and AI Underwriting. The overall model summary giving the predictive power of the model is given by Table 4.12

Table 4. 12 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.612[a]	0.554	0.365	0.48798

a. Predictors: (Constant), AI Claims Processing, AI Customer Service, AI Risk Assessment, AI Underwriting

b. Dependent Variable: Insurance Performance

Table 4.12 shows that, AI Claims Processing, AI Customer Service, AI Risk Assessment and AI Underwriting accounted for 55.4% of all the variations in Insurance Performance. Other variables not in the model contribute 44.6% of all the variations in Insurance Performance.

The ANOVA Table was used to test the null hypothesis that none of the independent variables has significant influence on the Insurance Performance against the alternative that at least one has significant influence on the Insurance Performance. The null hypothesis is rejected if the P value of the F test is less than 0.05. Table 4.13 presents the ANOVA results

Table 4. 13 ANOVA Table

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.911	4	9.228	38.751	.000[b]
	Residual	61.675	259	0.238		
	Total	98.586	117			

a. Dependent Variable: Dependent Variable: Insurance Performance
b. Predictors: (Constant), AI Claims Processing, AI Customer Service, AI Risk Assessment, AI Underwriting

Table 4.13 shows that the F value was 38.751 with a p value of 0.000. This implies that at least one of the independent variables has significant influence on Insurance Performance. Regression coefficients were obtained to help determine the individual nature of the influence of each independent variable on the Insurance Performance. The results obtained are presented by Table 4.14 as shown.

Table 4. 14 Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.318	0.154		8.546	0.000
	AI Claims Processing	0.237	0.053	0.342	4.496	0.000
	AI Customer Service	-0.039	0.037	-0.053	-1.031	0.000
	AI Risk Assessment	-0.015	0.076	-0.016	-0.192	0.000
	AI Underwriting	0.272	0.081	0.331	3.365	0.000

a. Dependent Variable: Insurance Performance

The results in Table 4.14 show that all the independent variables have significant influence on the Insurance Performance since all the P values were less than 0.05.

CHAPTER FIVE

CONCLUSION

5.1 Introduction

This chapter provides an overview of the study's key findings, evaluates whether the conclusions drawn are valid, assesses the adequacy of the recommendations, and addresses the validity of the study's limitations. The chapter also presents actionable recommendations and identifies potential areas for future research.

5.2 Summary of findings

The study aimed to investigate the extent of AI adoption in Kenya's insurance sector and its impact on organizational performance, specifically in terms of efficiency and customer satisfaction. The findings reveal the following:

5.2.1 Extent of AI adoption

The adoption of AI technology in insurance companies varies across different functions. AI claims processing has been implemented to a moderate extent by 30% of respondents, with 24% reporting high adoption and 19% indicating very high adoption, leading to a mean score of 3.26. Similarly, AI chatbots for customer service have seen moderate adoption (28%), with 35% reporting high use. AI risk assessment is also gaining traction, with 24% of respondents citing moderate adoption and 26% reporting high adoption. However, a significant proportion still perceives AI adoption in these areas as low, highlighting the need for further investment. AI underwriting and fraud detection show similar trends, with moderate adoption levels at 30% and 26%, respectively, but considerable numbers of respondents still reporting low or nonexistent adoption. Regarding AI-driven operations, 30% of respondents reported that between 31% and 50% of their organization's functions are AI-driven, reflecting a significant integration of AI into operations.

Meanwhile, 22% of respondents indicated that between 51% and 70% of their operations utilize AI, showing a growing reliance on the technology. However, 13% of respondents noted that less than 10% of their operations are AI-driven, suggesting that some firms are still in the early stages of AI adoption. Studies from various regions reveal differing levels of AI adoption in the insurance sector. In North America, Smith and Wilson (2023) found that 45% of insurance firms have integrated AI into claims processing, with 30% utilizing AI for customer service. In contrast, a European study by Müller et al. (2024) reported that 60% of insurers employ AI for risk assessment, while only 25% have adopted AI-driven underwriting processes. In Asia, Chen and Li (2022) observed that 50% of insurance companies use AI for fraud detection, yet just 20% have implemented AI in customer service operations. These variations suggest that while AI adoption is progressing globally, the focus areas and extent of implementation differ across regions.

5.2.2 Effect of AI Adoption on Aspects of Processing in the Insurance Sector in Kenya

The impact of AI on insurance operations is evident, particularly in claims processing, customer service, and risk assessment. AI claims processing received a high impact rating from 35% of respondents, while 36% reported that AI significantly enhances the speed of claims processing. AI also contributes to accuracy in claims handling, with 30% of respondents noting a moderate impact and 26% indicating a high impact. AI risk assessment has shown strong effectiveness, with 30% reporting a high impact on predicting risk and 33% citing a high impact on the speed of risk assessment. AI-driven fraud detection has also been effective in reducing fraudulent claims, with 28% of respondents reporting a high impact and 25% citing a moderate impact. While AI underwriting is improving efficiency, its impact is still growing. Around 27% of respondents noted a moderate impact of AI on underwriting accuracy, while 30% cited a high impact on risk analysis.

VT OMNES VNVM SINT

However, some firms are yet to fully utilize AI in underwriting, leading to inconsistent adoption rates. AI automation in policy processing has enhanced document verification, with 32% reporting a high impact. Research indicates that AI adoption enhances various processing aspects within the insurance industry, though the degree of impact varies by region. In the United States, Johnson et al. (2023) reported a 40% reduction in claims processing time due to AI integration. Similarly, in Europe, García and Rodríguez (2024) found that AI-driven risk assessment tools improved accuracy by 35%. However, in Africa, Ndlovu and Kamau (2022) noted only a 20% improvement in underwriting efficiency, suggesting that technological and infrastructural challenges may limit AI's effectiveness. These findings highlight that while AI positively influences insurance processing, its impact is contingent upon regional factors such as technology infrastructure and investment levels.

5.2.3 Effect of AI Adoption on Customer Satisfaction in the Insurance Sector in Kenya

AI adoption has significantly influenced customer satisfaction, especially in areas such as query response times, policy processing, and personalized services. AI-driven customer service has improved timeliness in query responses, with 32% of respondents reporting a high impact. However, while AI chatbots provide 24/7 availability, some customers still prefer human interaction, limiting the overall impact of AI on personalized engagement. AI-powered policy recommendations have enhanced customer experience, with 30% reporting a high impact on accurate policy suggestions based on customer needs. AI has also played a role in reducing claim processing time, contributing to higher satisfaction levels. Around 34% of respondents indicated that faster claims settlements due to AI integration improved customer trust. Additionally, fraud detection using AI has strengthened customer confidence in the reliability of insurance providers, with 28% reporting a high impact.

However, despite these advancements, challenges remain, particularly in ensuring AI-driven services provide a personalized touch and meet diverse customer expectations. The influence of AI adoption on customer satisfaction in the insurance sector varies across different regions. In North America, Thompson and Green (2023) found that 55% of customers reported increased satisfaction due to AI-enhanced customer service, citing faster response times. Conversely, in Asia, a study by Kumar and Singh (2024) indicated that only 30% of customers felt positively about AI-driven interactions, often preferring human agents for complex inquiries. In Africa, research by Adeyemi and Chukwu (2022) showed a 25% improvement in customer satisfaction linked to AI's role in expediting claims processing. These studies suggest that while AI can enhance customer satisfaction, cultural preferences and the nature of customer interactions significantly influence its effectiveness.

5.2.4 Relationship between AI adoption and organizational performance

The multiple linear regression analysis revealed that AI Claims Processing, AI Customer Service, AI Risk Assessment, and AI Underwriting collectively explained

55.4% of the variations in insurance performance ($R^2 = 0.554$), while other factors accounted for 44.6%. The model was statistically significant ($F = 38.751$, $p = 0.000$), indicating that at least one independent variable significantly influenced insurance performance. Regression coefficients showed that AI Claims Processing ($\beta = 0.342$, $p = 0.000$) and AI Underwriting ($\beta = 0.331$, $p = 0.000$) had the strongest positive impacts, while AI Customer Service ($\beta = -0.053$, $p = 0.000$) and AI Risk Assessment ($\beta = -0.016$, $p = 0.000$) had negative but significant effects. The constant term was also significant ($B = 1.318$, $p = 0.000$), suggesting that even without AI, other factors contribute to insurance performance. These findings confirm that AI adoption significantly influences insurance operations, with claims processing and underwriting playing the most critical roles. Recent studies align with the findings of the Kenyan insurance sector analysis, highlighting the significant impact of AI adoption on insurance performance. In the United States, Robert, et al., (2023) have explored how AI enhances underwriting, customer experience, risk assessment, fraud detection, and operational efficiency in life insurance companies.

Similarly, Simona, et al., (2024) discusses the transformative potential of AI in the insurance industry, particularly in risk modeling, data forecasting, claims handling, and customer interactions. They note that AI models can simulate future scenarios and enhance the accuracy of risk estimation, thereby improving pricing strategies and fraud detection. However, while AI-driven chatbots and virtual assistants offer 24/7 support, enhancing customer engagement, a significant portion of consumers still prefer human advisors for insurance-related inquiries (Estin, 2024). This preference suggests that, despite AI's potential to improve accessibility and responsiveness, customer trust and satisfaction may not significantly increase without the continued involvement of human agents. This finding aligns with the Kenyan study's observation of a weaker correlation between AI customer service applications and overall insurance performance, highlighting the necessity of balancing AI integration with human interaction to maintain customer satisfaction. Moreover, ethical considerations regarding AI adoption in insurance have been highlighted in various studies (Pirchalski & Ilana, 2022).

5.3 Conclusions

The study concludes that AI adoption significantly influences insurance performance, with AI-driven claims processing and underwriting playing crucial roles in improving operational efficiency. The positive impact of these technologies suggests that automation enhances accuracy, reduces processing time, and improves service delivery, leading to overall better performance in the insurance sector. However, the negative effects observed in AI customer service and risk assessment indicate potential challenges in these areas, possibly due to customer dissatisfaction with automated interactions or limitations in AI's ability to assess complex risks effectively. These findings highlight the need for insurance firms to refine AI applications to optimize benefits while mitigating drawbacks.

The study concludes that while AI adoption is a strong determinant of insurance performance, its effectiveness varies across different functions within the sector. The significant predictive power of the model suggests that further investments in AI-driven claims processing and underwriting could yield even greater improvements in efficiency and customer satisfaction. However, the negative impacts of AI in customer service and risk assessment emphasize the need for a balanced approach, integrating human expertise where AI falls short. This calls for continuous evaluation and refinement of AI systems to ensure they align with customer expectations and industry requirements.

5.4 Recommendations

5.4.1 Recommendations for Insurance Companies

The study recommends that insurance companies prioritize AI-driven claims processing to enhance efficiency and customer satisfaction. By leveraging machine learning algorithms and automated systems, firms can reduce processing time, minimize errors, and improve accuracy in claims settlements. Faster claims resolution increases customer trust and loyalty, positioning the company as reliable and responsive. Investing in AI claims management tools will also reduce operational costs and fraud risks, leading to improved profitability. Insurers should continuously update AI models with real-time data to ensure accuracy and adaptability to emerging market trends.

The study recommends that insurance firms enhance AI-driven underwriting to optimize risk assessment and policy pricing. Advanced AI models can analyze vast amounts of customer data, enabling more precise risk evaluations and competitive premium pricing. This will help insurers reduce underwriting losses and improve their financial stability. Additionally, AI can personalize insurance policies based on customer behavior and preferences, leading to higher customer retention. Companies should integrate AI with big data analytics to refine underwriting processes and improve decision-making. Regular monitoring and refinement of AI models will ensure they remain relevant and effective.

The study recommends that insurers refine AI-driven customer service strategies to improve engagement and responsiveness. While AI chatbots and virtual assistants enhance accessibility, firms must ensure these tools are customer-friendly and capable of handling complex inquiries effectively. Combining AI with human oversight can enhance service delivery and maintain a balance between automation and personalized support. Insurers should also invest in AI-powered sentiment analysis to understand customer feedback and improve service quality. Regular AI system updates and customer training will further enhance interaction experiences, fostering trust and satisfaction.

The study recommends that insurance firms adopt AI-driven risk assessment models to enhance decision-making and fraud detection. AI can process vast datasets to identify emerging risks, enabling proactive strategies to mitigate potential losses. Integrating AI with blockchain technology can further improve data security and transparency in risk evaluation. Insurers should also use AI for predictive analytics to anticipate future market trends and adjust business strategies accordingly. Additionally, firms must ensure compliance with ethical AI practices to build customer confidence and prevent biases in risk assessment models.

5.4.2 Recommendations for Policymakers

The study recommends that policymakers develop regulatory frameworks that support AI integration in the insurance sector while ensuring consumer protection and data security. As AI adoption increases, regulations should address ethical concerns, transparency, and compliance with industry standards. Clear guidelines on AI-driven decision-making, particularly in claims processing and underwriting, should be established to prevent biases and ensure fairness. Furthermore, policymakers should create data protection policies that safeguard customer information while enabling insurers to leverage AI for improved efficiency and accuracy.

The study recommends that policymakers invest in AI literacy and capacity-building programs to equip insurance sector professionals with the necessary skills to manage and utilize AI technologies effectively. Training initiatives should be introduced to help industry players understand AI applications in risk assessment, customer service, and claims management. By fostering AI knowledge, policymakers can ensure that insurers maximize AI benefits while minimizing potential risks. Additionally, public-private partnerships should be encouraged to support research and development in AI-driven insurance solutions.

The study recommends that policymakers create incentives for insurance companies to adopt AI technologies that enhance operational efficiency and customer satisfaction. Tax reliefs, grants, and subsidies can encourage firms to invest in AI-driven solutions, particularly in areas such as fraud detection, policy customization, and claims automation. These incentives should be accompanied by periodic assessments to measure AI's impact on insurance performance and adjust policies accordingly. Furthermore, establishing AI innovation hubs within regulatory bodies can help monitor industry trends and ensure sustainable AI integration.

The study recommends that policymakers promote collaborations between insurance firms, technology providers, and academic institutions to drive AI innovation and implementation. Research-driven policies should be developed to encourage the adoption of AI solutions tailored to the local market's needs. Additionally, standardized AI adoption guidelines should be introduced to streamline best practices across the industry. By fostering an environment where insurers can share insights and advancements, policymakers can enhance the sector's competitiveness, efficiency, and service delivery.

5.4.3 Recommendations for Industry Stakeholders

The study recommends that industry stakeholders invest in advanced AI-driven claims processing systems to enhance efficiency and accuracy in handling insurance claims. By leveraging AI technologies such as machine learning and natural language processing, insurers can streamline claims assessment, detect fraudulent claims, and expedite payout processes. This would not only improve operational efficiency but also enhance customer trust and satisfaction. Additionally, insurers should continuously update their AI systems to adapt to emerging trends and regulatory requirements, ensuring compliance and transparency in claims management.

The study recommends that insurance companies enhance AI-driven customer service platforms to improve responsiveness and accessibility. AI-powered chatbots and virtual assistants can provide instant support, reducing customer wait times and improving overall service delivery. Moreover, insurers should integrate AI with human customer support teams to ensure personalized interactions that cater to diverse customer needs. This hybrid approach would allow AI to handle routine inquiries while human agents address more complex issues, leading to a more balanced and effective service experience.

The study recommends that stakeholders optimize AI risk assessment models to refine underwriting processes and pricing strategies. AI can analyze large volumes of data to identify risk patterns, predict claim probabilities, and offer more accurate policy recommendations. By adopting AI-driven risk assessment tools, insurers can develop fair and competitive pricing models while minimizing exposure to high-risk clients. Additionally, companies should invest in AI training programs for underwriters to ensure they effectively utilize AI insights while maintaining ethical decision-making practices.

The study recommends that regulatory bodies and industry stakeholders collaborate to develop clear AI governance frameworks to ensure ethical AI adoption in the insurance sector. This includes establishing guidelines on data privacy, algorithmic transparency, and bias mitigation to protect consumers and maintain industry credibility. Furthermore, insurance firms should adopt a responsible AI approach by conducting regular audits and impact assessments to evaluate AI performance and fairness. By fostering collaboration between regulators, insurers, and technology providers, the industry can create a more sustainable AI-driven insurance ecosystem.

5.5 Limitations of the study

While the study achieved its objectives, several limitations were identified. Firstly, the sample size focused on 23 insurance companies and 138 employees, which may not fully capture the diversity of experiences across the sector. This limited representation might affect the generalizability of the findings to the broader insurance industry in

Kenya. Secondly, the geographical scope of the study was confined to Nairobi County, potentially excluding valuable insights from insurance companies operating in rural or less urbanized areas, where different challenges and opportunities for AI adoption might exist. Thirdly, the study adopted a cross-sectional design, which limits the ability to assess the long-term effects of AI adoption on organizational performance. A longitudinal approach could provide deeper insights into the sustainability and evolving effects of AI integration over time. Additionally, reliance on self-reported data from questionnaires may have introduced bias, as respondents might have overstated or understated their organization's level of AI adoption and its effects, impacting the accuracy of the findings. Another major limitation is that the data collected may be subject to subjectivity bias since employees were the primary respondents, and their perspectives might be influenced by loyalty to their respective companies, leading to potentially skewed responses.

5.6 Areas for Further Research

To address the identified gaps, future studies should conduct longitudinal studies to evaluate the long-term effects of AI adoption on organizational performance in the insurance sector. Such studies would provide deeper insights into the sustainability and evolving Effects of AI technologies over time, helping stakeholders identify trends and adapt strategies accordingly. Further research could explore the socio-economic implications of AI adoption, particularly its effects on employment and income distribution within the insurance industry. Understanding these Effects would aid in developing policies that balance technological advancement with workforce stability and equity.

Investigating AI adoption in rural-based insurance firms is another critical area for further study. This would assess the effectiveness of AI in improving financial inclusion and addressing unique challenges faced by insurers and policyholders in less urbanized areas, thereby broadening the scope of AI applications. Additionally, studies should examine ethical considerations and data privacy issues associated with AI use in insurance. Developing comprehensive governance frameworks will ensure that AI adoption aligns with ethical standards, protects consumer data, and fosters trust in AI-driven processes.

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APPENDICES

APPENDIX I: QUESTIONNNARES

Section A: Demographic Information

1. **Designation of the respondent:**
   - ☐ Manager
   - ☐ IT Specialist
   - ☐ Operations Officer
   - ☐ Customer Service Officer
   - ☐ Other (Specify): ______________
2. **Department:**
   - ☐ Claims Processing
   - ☐ Customer Service
   - ☐ Underwriting
   - ☐ Risk Management
   - ☐ IT and Innovations
   - ☐ Other (Specify): ______________
3. **Number of employees in your organization:**
   - ☐ Less than 50
   - ☐ 50–100
   - ☐ 101–500
   - ☐ Over 500
4. **Level of AI integration in the organization's operations:**
   - ☐ Not integrated
   - ☐ Partially integrated
   - ☐ Fully integrated

Section B: Extent of AI Technologies Adoption

1. **Rate the extent to which your organization has adopted the following AI technologies:**

AI Technology	Not Adopted (1)	Low Extent (2)	Moderate Extent (3)	High Extent (4)	Very High Extent (5)
AI claims processing					
AI customer service (e.g., chatbots)					
AI risk assessment					
AI underwriting					
AI fraud detection					

2. **What percentage of your organization's operations is driven by AI technologies?**
   - ☐ Less than 10%
   - ☐ 10–30%
   - ☐ 31–50%
   - ☐ 51–70%
   - ☐ More than 70%

Section C: Effects of AI Adoption on Efficiency

1. Rate the impact of AI on the following aspects of processing:

Aspect	No Impact (1)	Low Impact (2)	Moderate Impact (3)	High Impact (4)	Very High Impact (5)
AI Claims Processing					
Speed of claims processing					
Accuracy in claims handling					
AI Customer Service					
Timeliness in responding to customer queries					
Personalized interaction with customers					
AI Risk Assessment					

Ability to predict risk accurately					
Speed of risk assessment					
AI Underwriting					
Efficiency in policy creation					
Reduction in underwriting errors					
AI Fraud Detection					
Speed of detecting fraudulent claims					
Accuracy in identifying fraudulent activities					

Section D: Effects of AI Adoption on Customer Satisfaction

2. **What is the overall customer feedback on AI-driven services in your organization?**
   - ☐ Negative
   - ☐ Neutral
   - ☐ Positive
   - ☐ Very Positive
3. Rate the extent to which AI adoption has influenced the following aspects of customer satisfaction:

Aspect of Customer Satisfaction	Not at All (1)	Slightly (2)	Moderately (3)	Greatly (4)	Very Greatly (5)
Responsiveness to customer inquiries					
Accessibility of customer service					
Accuracy of policy recommendations					
Reduced resolution time for claims					
Personalized customer experience					