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Assessment of the fraud detection technologies used by Kenyan insurance firms in detecting and preventing fraudulent insurance claims.

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ASSESSMENT OF THE FRAUD DETECTION TECHNOLOGIES USED BY KENYAN INSURANCE FIRMS IN DETECTING AND PREVENTING FRAUDULENT INSURANCE CLAIMS

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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DEDICATION

I dedicate this research thesis to my late father Samuel Owuor Agot and my mother Monica Achieng Owuor for her support and encouragement during my entire study period.

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ABSTRACT

Insurance plays a vital role in the growth of economies, including Kenya's, as it serves as a mechanism to replace losses, which promotes sustainable economic development. Unfortunately, fraudsters have recognized the insurance industry's liquidity and susceptibility to fraud, leading to a significant influx of fraudulent activities. This has prompted insurance companies to employ advanced technology to detect and prevent fraudulent insurance claims. The goal of this research was to identify the fraud detection technologies that Kenyan insurance companies are employing to identify fraudulent claims, the firm characteristics that influence the selection of technologies, and the firms' perspectives on the efficiency of contemporary technologies in the identification of fraudulent insurance claims. The study employed a descriptive survey, and the data was collected through questionnaires. The population of the study was 56 licensed insurance firms in Kenya**,** as reported by IRA in 2021. It was established that the common fraud detection technologies include the Internet of Things (25.5 percent), machine learning (17.6 percent), artificial intelligence (17.6 percent), and blockchain (5.9 percent). Nonetheless, the insurance companies were using other forms of fraud detection (33.3 percent). The type of Insurance by-products is positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. The combined ratio and size of the insurance company positively and statistically influence the adoption and implementation of fraud detection technologies by insurance companies. Board size and board independence are positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. However, board gender diversity is not a significant predictor. The study concludes that the Internet of Things was the most popular technology used by Kenyan insurance firms to detect and prevent fraudulent insurance claims, followed, by machine learning, artificial intelligence, and blockchain. A conclusion is further made that the type of insurance by-products influences the adoption and implementation of fraud detection technologies. The size of the insurance company, profitability, board size, and board independence are significant company characteristics that influence the adoption and implementation of fraud detection technologies. Insurance detection technologies are useful and efficient in detecting fraudulent insurance claims. The study recommends the deployment of more than one technology informed by the different nature of fraud claims and dynamics associated with fraudsters and detection technologies. Before implementing any insurance fraud detection technology, the insurance company needs to consider the kind of insurance products it is dealing with. Moreover, profitability and company size define the ability of the insurance company to implement fraud-detecting technologies. There is a need for an effective board in the implementation of fraud detection technologies by insurance companies. With increasing insurance fraud claims, insurance companies ought to implement fraud detection technologies that suit the needs of the organization. The needs are parametrized by the usefulness and efficacy of the technologies in detecting fraudulent insurance claims.

Keywords. *Fraudulent Insurance Claims, Insurance Fraud, Machine Learning, and Artificial Intelligence.*

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LIST OF ABBREVIATIONS.

A.I. - Artificial Intelligence

AAR- Africa Air Rescue

ABI- Association of British Insurers

AKI- Association of Kenya Insurers

APA- Apollo Life Assurance

ASISA- Association for Savings and Investment South Africa.

CAGR- Compound Annual Growth Rate

CIC- Co-operative Insurance Company

COVID-19- Corona Virus Disease 2019

FBI- Federal Bureau of Investigation.

GDP- Gross Domestic Product.

GWP- Gross Written Premium

HICs- Health Insurance Claims

ICT- Information Communication Technology

IDT- Innovation Diffusion Theory

IDT- Innovation Diffusion Theory

IFIU- Insurance Fraud Investigation Unit

III- Insurance Information Institute.

IoT- Internet of Things.

IRA- Insurance Regulatory Authority

ML- Machine Learning

NACOSTI- National Commission for Science and Technology Information

NAIC- National Association of Insurance Commissioners

NHCAA- National Health Care Anti-Fraud Association

NIC- National Insurance Commission

OECD- Organization for Economic Cooperation and Development.

PEU- Perceived Ease of Use

PU- Perceived Usefulness

ROI- Return on Investment

RPA- Robotic Process Automation.

SUEC- Strathmore University Ethical Committee

TAM- Technology Acceptance Model

UGX- Ugandan Shilling.

USD- United States dollar.

UTAUT- Unified Theory of Acceptance and Use of Technology

CHAPTER ONE
INTRODUCTION TO THE STUDY

1.1 Background to the study

Technology assumes a broad scope that touches all aspects of business, especially the insurance industry. According to Kurtz and Koone (2009), big data mining and the emergence of artificial intelligence (AI) have greatly impacted the market's focus from sellers to buyers. Big data and artificial intelligence backed by technology produce precise information about clients, product specifications, and preferences (Gelernter**,** 2016). Salatin (2014) asserts that using ICT in the insurance sector will result in greater production capacity, activity specialization, and service speed and quality improvements. In general, electronic insurance gives customers remote access to safe intermediaries that enable them to obtain insurance services.

Kerinet (2006) argues that technology promotes sustainable environmental development through awareness and access to information, empowers businesses to make positive contributions, and takes social responsibility for the environment. Fidelia (2019) studied the application of ML for estimating motor vehicle insurance premiums. The research explored the applicability of new ML techniques, such as tree-boosted models, in optimizing the premium of policyholders. Their study proposes two machine learning models for pricing motor vehicle damage insurance (decision trees and regression).

Utilizing novel and unstructured data sources is now possible thanks to artificial intelligence and machine learning developments (Battina, 2017). Due to the limited number of data sources, such as national I.D. systems, credit histories, and web activity, developing markets must be more inventive in finding and utilizing unique datasets. According to Chummun (2018), the microinsurance value chain is susceptible to hazards like fraud, where A.I. could aid with risk modeling, pricing, collection frequencies, customer acquisition, distribution, and eventually, fraud detection.

Insurance providers and consumers are impacted by insurance fraud, which is a serious problem because insurers frequently try to offset fraud losses by raising premiums (Aslam, et al., 2022). The general assumption is that suspicious activity is increasing, fraudsters' strategies are becoming considerably more sophisticated, and the battle against fraud has been moving to the digital sphere since the beginning of the COVID-19 pandemic (Gupta, et al., 2021). The key to stopping fraudulent actions before real harm is done is to be vigilant and have anti-fraud technology to detect suspicious activities early on; as a result, anti-fraud leaders must make the

difficult decision to increase budgets to continue investing in well-known and dependable tools like automatic monitoring and procure newer anti-fraud solutions and techniques like Blockchain and identity verification technology (Coalition Against Insurance Fraud, 2021)

While these changes can initially be accompanied by fear and doubt, innovation through new technology is a fundamental driver of change in the financial sector, leading to incalculable efficiency improvements. Such innovation has recently occurred due to new technology advancements, frequently referred to as "Fin-Tech" (OECD, 2017). The emergence of new technologies, including cloud computing, the Internet of Things (IoT), advanced analytics, mobile devices, Blockchain, smart contracts, and artificial intelligence, has opened up new opportunities for measuring, controlling, and pricing risk as well as for customer engagement, cost reduction, increased efficiency, and expansion of insurability (Ferenzy, 2016).

Technology enhances corporate operations, boosts productivity, and enables more efficient resource allocation and use. Technology advancements in knowledge, skills, computers, systems, and social media aid in the growth of customer relationships and enhance customer confidence in the services offered by insurance companies (OECD, 2017). Most companies have resorted to machine learning (ML), predictive analytics, and data mining techniques to strengthen fraud detection (Mansour, 2020). An important development in cybersecurity efforts has been anomaly detection (ML) models to create a baseline to understand typical claims in insurance fraud. Once that baseline has been established, they can spot anomalies and notify insurers.

Soraite (2009) stated that technology is one of the company's functional strategies, and together they make up the business strategy. In his study on the impact of technology on the performance of insurance firms in Kenya, Nyakundi (2020) contented that continuous use of technology has led to enhanced performance. Technology helps firms to carry out their operations without much paperwork efficiently.

To conduct a study on the state of insurance technology in 2021, the Coalition Against Insurance Fraud polled its respondents about the fraud-detection systems and anti-fraud technologies that companies are now using as part of their anti-fraud campaigns. The study discovered an increase in the use of anti-fraud technologies to identify false claims, fraudulent underwriting, and internal fraud (Cappiello, 2020). The study also found that 4 out of 10 respondents are now using Identity Verification Solutions, a new anti-fraud technique. The study also concluded that most insurers would likely adopt blockchain technologies and other

digital identity solutions in the next three to five years (Coalition Against Insurance Fraud, 2021). More than 35% of insurers said they used photo recognition and analytics in 2021 to combat fraud. As more insurers want to cut costs by avoiding in-person inspections of minor residential and commercial property claims as well as claims for vehicle property damage, photo recognition & analysis are becoming increasingly crucial (Verma, 2022). With the aid of this technology, insurers may determine whether a photo of alleged damage is authentic, has been digitally manipulated, or has already been filed for other claims. Through picture data processing, photo recognition technology enables worldwide image search and even the detection of little modifications or adjustments in a photo that the human eye cannot see.

According to McKinsey, Africa is one of the world's most attractive regions for insurance. According to his analysis, the Continent is now the second-fastest-growing region for insurance internationally, behind Latin America, due to consistent economic growth in most of its member states and a largely undeveloped insurance industry (OECD, 2022). Before the Corvid-19 epidemic, it was predicted that the African insurance market would expand at a compound annual growth rate (CAGR) of 7% from 2020 to 2025, which would be twice as fast as North America, more than three times as fast as Europe, and six times faster than Asia (Bagus, 2020).

The Gross Written Premium (GWP) of the insurance sector in Africa is estimated to be at $68 billion, less than other emerging markets like Latin America and the Caribbean. The Continent's adoption is extremely uneven, with just ten countries accounting for 91% of premiums, with South Africa having the Continent's largest and most developed insurance market (McKinsey, 2020). Furthermore, McKinsey claims that over the past five years, most African nations have seen double-digit CAGR insurance growth in local currency, primarily due to economic expansion rather than deeper market penetration (OECD, 2022). When expressed as a proportion of GDP, Africa's insurance penetration levels are half that of the rest of the world, and its per-capita premium costs are 11 times less.

The continent of Africa has a variety of distribution channels for both life and non-life products, based on regions. The most popular channels are brokers and agents, but direct sales and shares of ban assurance have also greatly expanded (McKinsey, 2020). Oundo (2019) researched the use of machine learning algorithms in the healthcare industry. He claimed that by utilizing techniques like logistic regression and SVM, he was able to identify claims as being correct or needing further investigation by auditors. Africa Trade Insurance's 2021 annual report shows that Safaricom Limited has taken up insurance worth USD 444 million (KES 52.9 billion) for

M-Pesa, which is insurance coverage against the risk of non-payment or default on payments of M-Pesa-related loans.

According to IRA, the insurance sector in Kenya generated gross premiums of KES 234.78 billion in 2020 (2019: KES 229.50 billion), representing a nominal growth of 2.3% (-2.9% in real terms). Kenya finished fourth behind South Africa, Morocco, and Egypt in terms of gross premium income in Africa. In 2020, the industry's net profit fell sharply by 57.7%, from KES 15.12 billion to 6.39 KES billion. Kenya's insurance penetrations (the ratio of gross direct insurance premium to GDP) decreased from 2.34% in 2019 to 2.17% in 2020. The average insurance penetration rate across the globe was 7.4%. Insurance spending declined slightly from KES 4,788 in 2019 to KES 4,787 in 2020, as measured by insurance density (the ratio of gross direct insurance premiums to the entire population) (IRA, 2020).

1.1.1 Fraudulent Insurance Claims.

Insurance fraud refers to a deliberate deception carried out against or by an insurance company or agent. It can be committed by applicants, policyholders, third-party claimants, service providers, brokers, or company staff (Kowshalya & Nandhini, 2018). Common forms of fraud include exaggerating claims, lying on insurance applications, filing false claims for non-existent damage or injuries, and staging fake accidents (III, 2022). Organized criminals who steal significant sums through fraudulent business practices, practitioners and specialists who inflate service costs or charge for services not provided, and regular people who want to charge their deductible or see filing a claim as a chance to make a little extra money are the people who commit insurance fraud, according to the Insurance Institute of Information.

According to Opiyo (2013), misrepresentation presents a genuine commercial opportunity and a significant challenge for the conservation industry because fraud-related losses impact the conservation industry's growth. Insurance fraud is the false portrayal of a self-evident fact, whether via words or deeds, false or misleading assertions, or the concealment of what should have been made clear, that deceives and is intended to defraud another person so that they will pursue it for their actual harm (Clemency, 2002). The relationship between guarantors and policyholders is also threatened by insurance fraud because it depletes the store pooled from the assured (Yusuf, 2009).

Duffield and Grabosky (2001) consider cheating to be unlawful, and it has a duality (e.g., deliberately twisting reality, distorting or obscuring important certainties). Contained, gaining an unfair advantage over others, the ultimate goal is to maintain surveillance and deny someone

else's rights about something of great value. However, the most befitting definition is the one advanced by Derrig (2002) which characterized insurance fraud as an unlawful act that entails obtaining monetary benefit through the misrepresentation of an actual position for financial gain; this is because the main objective of fraud is to achieve financial benefits.

A study by The Coalition Against Insurance Fraud in 2022 revealed that insurance fraud results in an annual cost of $308.6 billion for American consumers. This total incorporates yearly fraud estimates for various liability sectors, such as life insurance ($74.7 billion), property and casualty ($45 billion), workers' compensation ($34 billion), and auto theft ($7.4 billion). The overall cost of insurance fraud (non-health insurance) is projected to be more than $40 billion annually in America, according to the FBI, which puts this into context. This suggests that rising premiums caused by insurance fraud cost the typical American family between $400 and $700 annually. According to Lazic (2023), fraud accounted for around 10% of all claim's costs in the United States. The ABI in 2020 noted that insurers in Europe discovered 96,000 fraudulent insurance claims totaling £1.1 billion. Additionally, they predicted that a comparable amount of fraud goes undiscovered annually, which is why insurers spend at least £200 million annually to detect fraud.

According to a 2017 Verisk study, auto insurance companies lose a minimum of $29 billion annually due to premium leakage, which is defined as "omitted or misstated underwriting information that leads to inaccurate rates, several types of information failure and fraudulent practices drive the cost up," including "unrecognized drivers ($10.3 billion), underestimated mileage ($5.4 billion), violations/accidents ($3.4 billion), and false garaging to lower premiums ($2.9 billion)". Additionally, according to the National Health Care Anti-Fraud Association (NHCAA), there may be up to $300 billion in financial damages due to healthcare fraud. In India, fraudulent health insurance claims have risen to 35 percent in 2022 up from 23% in 2021 with many insurance companies suffering a loss of up to 15 percent of their business revenue (Suseel & Rastogi, 2022).

According to the Association for Savings and Investment South Africa (ASISA), South African life insurers found 4287 dishonest and fraudulent claims totaling R787.6 million across all lines of risk business in 2021, an increment from 3186 instances in 2020 that resulted in claims totaling R587.3 million. Death insurance, disability insurance, hospital cash plans, and retrenchment benefit insurance in South Africa had the greatest rates of fraud and dishonesty (ASISA, 2021).

According to the 2019 Annual Report of the National Insurance Commission (NIC), 25% of insurance claims in Ghana are fraudulent; the report indicated that non-medical insurance fraud was estimated at $40bilion per year. Elsewhere in Uganda, IRA of Uganda reported that in 2021 a total of 23 suspected fraudulent insurance claims were reported; 11 were forgeries and issuing fake documents. The unit received and investigated fraud reports worth UGX 11,230,175,000 during the year 2021 (IRA, 2021).

According to IRA, 127 incidents of insurance fraud were discovered in Kenya in 2020 as opposed to 83 cases in 2019, according to information submitted by the Insurance Fraud Investigation Unit (IFIU). Fraudulent motor insurance claims and theft by insurance agents accounted for 39 (30.7%) and 23 (18.1%) fraud cases in 2020, respectively. While medical fraud's value decreased from Sh42.1 million to Sh1.5 million, vehicle fraud's value fell from Sh52.8 million to Sh12.1 million (IRA, 2020). According to IRA data, insider fraud at insurance companies increased 13.4 times, from Sh19.2 million in 2019 to Sh258.4 million in 2020. Recent false medical claims cost the National Hospital Insurance Fund more than $100 million (Ombati, 2019). According to Cytonn (2022), fraudulent claims in the motor industry accounted for 25.7 percent while forgery was 13.5 percent. The sector has been adopting the use of blockchain and artificial intelligence to curb fraud within the sector. The Financial Fortune (2021) estimates more than 40 percent of motor vehicle insurance policies in Kenya are fraudulent. Furthermore, IRA (2022) indicated that medical insurance raised concerns over rising collusion between medical doctors and pharmaceutical firms to fleece health insurers who recorded underwriting losses of Sh628.58 million in the first quarter of 2021 compared to a profit of Sh11.59 million in a similar period in 2020.

1.1.2 Insurance Fraud Detection Technologies

Historically, the insurance sector has relied on manual methods and human expertise to identify and investigate potential fraudulent insurance claims (Abdallah, et al., 2016). However, the advent of fraud detection technologies has revolutionized the detection of fraudulent claims, making it more efficient, precise, and timely. Sungadhi (2008) suggests that technology enhances customer relations management by improving reliability, incorporating valuable customer feedback, implementing monitoring protocols, and facilitating data analysis. Thomas and Hughes (2004) define technology as the collection of systems, skills, and knowledge employed by businesses to manufacture goods and provide services. This characterization often portrays technology as a problem-solving tool.

In the property and casualty insurance industry, fraud detection technologies play a crucial role, especially in detecting fraudulent insurance claims, as part of the sector's digital transformation (Li, et al., 2022). Insurance companies are utilizing technologies such as AI, big data, and robotic processing automation to enhance their operations and provide speedy settlements to meet the growing expectations of customers. However, as insurers strive to expedite the claims process, they may be exposing their businesses to fraudulent activities. The Insurance Information Institute (2021) revealed that insurance claim fraud amounts to a $30 billion and perpetrators are utilizing sophisticated techniques to deceive insurance companies. While anti-fraud technology has made significant strides, insurers must adopt new technologies on a larger scale to minimize their losses.

Sadgali et al. (2019) suggested that adopting technology throughout the insurance value chain, including product innovation, underwriting, and distribution, can provide insurers with access to more data, allowing them to make sense of trends. This data can be leveraged to develop measures to detect and prevent fraud, leading to a decrease in fraudulent claims. Data analytics is one of the critical technologies employed to identify fraudulent insurance claims. By scrutinizing extensive datasets, insurers can identify anomalies and patterns that could suggest fraudulent activity (West & Bhattacharya, 2016). For instance, if a person submits multiple claims for the same loss within a short period of time, data analytics can detect this activity as potentially fraudulent. Artificial intelligence is another technology used to identify fraudulent insurance claims. A.I algorithms can learn from past fraudulent claims, enabling them to quickly recognize potential fraudulent claims. This technology is particularly useful in detecting more intricate fraud schemes that may be challenging for human analysts to detect. Blockchain technology is also used in detecting fraudulent insurance claims, by providing an unalterable ledger that documents all transactions related to an insurance policy, blockchain technology can help insurers detect fraudulent activities (Oberoi & Kansra, 2022). For example, if an individual submits a claim for an event that never happened, blockchain technology can detect this by verifying the accuracy of the claim.

According to Clark (2021), the rise of remote claims inspections has been a significant change in the past year due to the pandemic. However, fewer onsite visits have resulted in fraudsters taking advantage of the situation to profit. To combat this, insurers are taking precautions by using advanced anti-fraud technology, including digital forensic capabilities, proactive analytic solutions, and flagging synthetic identities. By incorporating advanced fraud detection technology into their digital initiatives, insurers can protect themselves against evolving fraud

schemes. According to a report by Allied Market Research (2021), the insurance fraud detection market is predicted to grow significantly due to the increasing need for insurance companies to detect and prevent fraud. The report emphasizes that fraud detection technologies, such as Artificial Intelligence (AI), blockchain, and machine learning, are becoming essential tools for insurance companies in detecting fraudulent claims. Tian (2017) noted that data mining methodologies, technologies, and algorithms have helped insurance firms to effectively detect fraud, improve the efficiency of risk management, and reduce unnecessary costs massively. Njeru (2022) established that machine learning showed promising results in detecting fraudulent vehicle insurance claims at 84.5 percent accuracy.

IoT is a network of physical items connected to and exchange data with other systems and devices through the internet. Machine learning has also been widely used in fraud detection within the insurance industry. ML algorithms can analyze large amounts of data to identify potentially fraudulent activities by identifying patterns and anomalies in data. With Artificial intelligence, AI algorithms analyze large amounts of data to identify patterns that indicate potentially fraudulent activities. According to Li et al. (2018), AI algorithms can be used to detect fraudulent claims by analyzing the claimant's behavior patterns, such as claim frequency, location, and history. A blockchain data format makes it possible to create a digital log of transactions and share it among a distributed network of computers. The decentralized nature of blockchain technology has the potential to reduce fraudulent activities by providing a secure and transparent platform. According to Zheng et al. (2018), blockchain technology can help in preventing fraud by allowing insurers to access a shared database of claims data, which reduces the possibility of duplicate or false claims.

1.1.3 Insurance Firms Characteristics.

The implementation of fraud detection technologies in the insurance sector is affected by varied salient features of the firm (Aslam, et al., 2022). Some of the features include profitability (Gartner, 2022), size of the insurance firm (Surinac et al., 2009), insurance products (Segodi & Sibindi, 2022), and corporate governance characteristics (Persico, 2019).

Profitability is a measurement of a company's earnings in relation to its expenditures (Gartner, 2022). More effective businesses will make more money relative to their costs than less effective businesses, which must spend more to make the same amount of money. A profitable insurance company is likely set aside earnings to acquire, install and maintain fraud detection

technologies (Copeland, 2022). The fraud detection technologies are cost-intensive in terms of the acquisition of the fraud detection technologies, operations, and maintenance.

The adoption of any new technology and the size of an insurance company significantly impact which fraud detection methods it chooses to implement. Large insurance companies in terms of assets are more likely to resolve the development or acquisition of fraud detection technologies (Kijkasiwat & Phuensane, 2020). Market-leading companies are more inclined to embrace new technologies because they are better positioned to reap the benefits of doing so. Furthermore, bigger and more profitable enterprises are more likely to have the monetary resources necessary for procuring and installing a new technology even amid inefficient capital markets (Nguyen et al., 2022). In terms of risk distribution, large insurance companies can distribute risks, associated with new initiatives since they have more options when it comes to which technologies to implement and can test out new ones without having to shut down their existing ones.

The type of insurance products that an insurance company deals with is likely to influence the adoption and implementation of fraud detection technologies. For instance, general and motor insurance products are likely to record high cases of fraud claims compared to health and life insurance. Thus, the type of insurance products that are prone to fraud claims will likely prompt the insurance companies to seek claim fraud detection technologies. According to IRA (2022), insurance products in the Kenyan market include, and not limited to, auto insurance, general insurance, medical insurance, life insurance, fire insurance, and aviation insurance. Segodi and Sibindi (2022) noted that types of insurance products experience different levels of fraud claims and the type of mitigation strategies.

The prevention and detection of fraud within insurance firms is primarily the responsibility of the management under the oversight of those charged with governance (Rohmatin, et al., 2021), Auditors, along with other members of the corporate governance and reporting ecosystem, also have an important role. There is an opportunity for all involved – including management and boards, auditors, and regulators – to focus more on corporate culture and behaviors to support fraud detection. According to Rohmatin, et al. (2021), corporate governance plays a critical oversight in the organization and is thus important in fraud detection and prevention mechanisms. Likewise, Maravelaki, et al. (2021) indicated that the board of management paves the way for the implementation of technological processes in an organization.

1.1.4 Kenya Insurance Industry and Usage of Insurance Fraud Detection Technologies

Commercial banks, microfinance, and insurance firms make up the Kenyan financial market. The insurance industry is considered one of the essential sectors for economic growth as it contributes significantly to the country's GDP (Njeru, 2022). Due to financial risk exposure, the economy may not grow vibrantly without the insurance industry. Insurance is important as it works as a shock absorber, giving investors' confidence in making financial investments with risk factors (Gisairo, 2016). The insurers always indemnify the policyholders whenever they incur losses on their assets insured. Investors can always place covers by intermediaries or direct.

Insurance companies are essential in protecting oneself and loved ones from financial distress caused by life's uncertainties, such as health issues, accident issues, or sudden loss. These firms can help with financial support or security when these problems occur. In a situation where a loss has occurred, investigators, assessors, loss adjusters, surveyors, and brokers will help the insurance firm assess the loss level and ascertain that the policyholder's negligence did not cause the loss. They also help in claim processing and settlement. The entire process of insurance, from taking the policy, and administering the policy to compensation when a loss occurs, is regulated by Insurance Regulatory Authority which is the body authorized to regulate insurance operations in Kenya.

According to IRA (2021), there were 11,273 licensed insurance players in 2020 compared to 10,471 licensed insurance players in 2019, including 26 agents carrying out banc assurance. Further, according to the regulator, there were 56 licensed insurance companies as of December 2021 offering various products and services. According to AFRIKTA (2022), some of the best and top insurance firms in Kenya are Jubilee Insurance Company, Britam Insurance Kenya, CIC Group Insurance, AAR Insurance Kenya, Maddison Insurance Kenya, First Insurance Kenya, Resolution Insurance Company Kenya, and Kenya Alliance Insurance Company. Almost all these companies operate in the same line of business: life, medical, and general insurance.

In 2022, Mwango Capital a financial research firm conducted a study on the general insurance market in Kenya and identified the three leading insurance companies in terms of market share, these companies are APA Insurance Company, with a market share of 9.35%, Old Mutual General Insurance, with a market share of 9.29%, and G.A. Insurance Company, with a market share of 8.73%. According to IRA, fraud is the major setback the insurance providers are

facing; this has increased the cost of doing business and threatens the survival and existence of these noble service providers. If fraud is not detected early, it will have huge financial implications, and because it is white-collar in nature, eliminating it may be an impossible and costly affair (Makove.s, 2015), Companies are extremely threatened by this fraud risk as it can drive them out of business and reduce their competitive advantage. Fraud affects companies in many ways, i.e., operation, financial, reputational, and relationship with other stakeholders in the industry. The greatest effects of fraud for these companies are loss of funds and customer confidence which can result in customers withdrawing from insurance policies.

According to AKI (2021), fraudulent motor insurance claims and theft by insurance agents accounted for 30.7% and 18.1% of fraud cases in 2020, respectively. According to Cytonn (2022), fraudulent claims in the motor industry accounted for 25.7 percent while forgery was 13.5 percent. Due to the rising fraudulent claims in the insurance industry, insurance companies decided to adopt fraud detection technologies to tame the menace (Cytonn, 2022; AKI, 2022). However, it is not clear through empirical studies which fraud detection technologies have been adopted most by the insurance companies and what factors influence the likelihood of the insurance company adopting fraud detection technologies.

1.2 Research Problem

Fraudulent insurance claims have rocked the insurance industry in Kenya. The Financial Fortune (2021) estimates more than 40 percent of motor vehicle insurance policies in Kenya are fraudulent. False medical claims cost the National Hospital Insurance Fund more than $100 million (Ombati, 2019). Furthermore, IRA (2022) indicated that medical insurance raised concerns over rising collusion between medical doctors and pharmaceutical firms to fleece health insurers who recorded underwriting losses of Sh628.58 million in the first quarter of 2021 compared to a profit of Sh11.59 million in a similar period in 2020. There were 127 insurance fraud cases in Kenya in 2020 compared to 83 reported cases in 2019, worth 327.7 million during the Corvid-19 pandemic. The most frequent fraud cases in 2020 were in motor insurance claims (30.1%), theft by insurance agents (18.1%), and medical insurance (9.4%) (IRA, 2020). These fraudulent activities are normally carried out by clients, employees, or collusion between individuals within and outside the organization.

Insurance companies have been deploying insurance fraud detection technologies to detect and prevent fraudulent claims. The sector has been adopting the use of blockchain and artificial intelligence to curb fraud within the sector. According to Cytonn (2022), insurance companies

in Kenya have been adopting the use of blockchain and artificial intelligence to curb fraud within the sector. AKI (2022) noted that insurance companies have set up measures including technology to combat motor and medical frauds which have been the biggest problem in the sector. In 2021, the AKI launched a mobile platform for filing accident claims in a push to cut back on motor fraud, reducing instances of fraud where motorists would collude with the police to alter the circumstances of an accident. However, it is not clear through empirical research what specific characteristics of insurance companies influence the desire by insurance companies to adopt and implement insurance fraud detection technologies and whether the insurance fraud detection technologies are effective enough to detect fraudulent insurance claims.

In a study to determine the effects of Technology Adoption on the underwriting process among the top 5 insurance companies in Nairobi County, Ngiri (2021) concluded that digitization of the claims process, digital fraud detection, and customer relationship management system factors significantly affected the underwriting among top insurers. However, the study focused on the effect of technology use on the performance of insurance companies contrasting the current study that focuses on investigating the fraud detection technologies used in the insurance industry in Kenya and the firm's salient characteristics that influences the adoption of these fraud detection technologies presenting a conceptual gap. Similarly, Nyakundi (2020) determined the effect of technology on the performance of insurance companies in Kenya but did not identify the key fraud detection technologies. Furthermore, it did not pinpoint the key salient insurance company features that influences the adoption of insurance fraud detection technologies presenting a conceptual gap. A study by Kajwang (2022) on implications for big data analytics on claims fraud management in the insurance sector concluded that Big Data Analytics in the insurance industry is becoming a promising field for gaining insight from very large data sets, enhancing outcomes, and lowering costs. However, the study was a literature review and failed to quantitatively identify the fraud detection technologies being used by insurance companies in Kenya. This study using a descriptive cross-sectional survey sought to quantitatively identify the fraud detection technologies being used by insurance companies in Kenya presenting a methodological gap. A study by Mushunje (2019) focused on fraud detection and fraudulent risk management in the insurance sector using selected data mining tools in Zimbabwe. The deployment of fraud detection technologies is affected by different regulatory frameworks that exist in different countries. Moreover, the manifestation and dynamics of insurance fraud claims may vary across regions and countries because of different

factors presenting contextual gaps. It is against this that the study sought to investigate the fraud detection technologies used by insurance companies in Kenya to detect fraudulent insurance claims and the salient insurance firm features that influence the adoption of fraud detection technologies.

1.3 General Objective.

The study's general objective was to establish the fraud detection technologies used by insurance companies in Kenya to detect fraudulent insurance claims.

1.3.1 Specific Objectives of the Study.

i. To establish the fraud detection technologies used by Kenyan insurance firms to detect fraudulent insurance claims.
ii. To examine how specific characteristics of insurance companies influence the adoption and implementation of fraud detection technologies.
iii. To establish the perspectives of insurance companies on the usefulness of modern technologies in detecting fraudulent insurance claims

1.4 Research Questions

i. Which fraud detection technologies are being used by Kenyan Insurance firms to detect fraudulent insurance claims?
ii. Do specific characteristics of insurance companies influence the adoption and implementation of fraud detection technologies?
iii. How effective are fraud detection technologies, such as machine learning Internet of things, blockchain, and artificial intelligence, in detecting fraudulent insurance claims,

1.5 Significance of the Study

This study is of great importance to the insurance industry in Kenya and beyond Kenyan borders.

1.5.1 Insurance Companies

The study results may help firms create operational plans and systems, new product development strategies, market penetration strategies, and resource allocation and utilization strategies that are both effective and efficient. It may also help insurance managers make a proper and guided decision on which technology to install to detect fraudulent insurance claims and improve performance effectively. The study may also help insurance firms know factors that should be considered while choosing the technology to invest in to avoid making biased

investment decisions. Furthermore, insurance companies can deploy effective fraud detection technologies that suit the needs of the company and the products the company deal with. The products that insurance companies deal with are differently targeted by fraud claims and thus the insurance company will be able to deploy fraud detection technologies that suit their needs.

The outcomes may make it easier for each insurer to comprehend where they stand in the campaign against insurance fraud. Some may attempt to enhance current fraud control techniques, while others could think about completely overhauling current strategies. This study tries to show how important it is to use the right technology to fight insurance fraud. Additionally, the study may examine the variables that affect the technology that insurance firms choose to deploy as well as their perception of the technology's value in identifying fraudulent claims.

1.5.2 Researchers

The study aim was to assess the fraud detection used by Kenyan insurance firms in detecting and preventing fraudulent insurance claims has significant implications for researchers. The study adds to the existing body of knowledge on fraud detection and prevention in the insurance industry, enabling researchers to identify gaps in knowledge and develop new theories, the study may serve as a benchmark for future studies on fraud detection and prevention in the insurance industry, allowing researchers to compare the use of technologies in other countries or industries. Ultimately, the study contributes to the advancement of knowledge and informs policy and practice in the insurance industry, supporting innovation and development.

1.5.3 Regulators

The Insurance Regulatory Authority (IRA) may particularly benefit from this study because it may help them formulate policies and regulations for the insurance sector, whose working environment is constantly changing. The findings may also provide a perspective that may help policymakers identify the areas in need of policy revision, re-formulation, and implementation, as well as ongoing review. Regulatory may also formulate or review policies that guide the deployment of fraud detection technologies in the insurance sector. This will promote the use of fraud detection technologies to combat fraud claims in the insurance sector.

1.5.4 Investors and General Public

The study may tell investors or the general public about the technologies that the insurance firms in Kenya are using to detect and prevent insurance fraud. The study may enable the investors to know the insurance companies that are prepared to fight and prevent insurance fraud which will, in turn, reduce the instances of insurance losses, enabling them to form good investment decisions when it comes to insurance investment. The study may also help to raise the trust and confidence of individuals in insurance companies as the results indicate that the fraud detection technologies used by the insurance companies are effective in detecting insurance fraud and vice versa.

1.6 Scope of the Study.

The study was limited to 56 licensed insurance firms in Kenya. The study is interested in establishing the technologies currently used by insurance firms in Kenya and their effectiveness in detecting fraudulent insurance claims. The researcher looked into the fraud detection used by insurance companies in Kenya and if they are effective in detecting fraud, as well as looked into factors that influence the choice of technology used by these financial institutions.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of various literature, in line with the study objectives, which are to establish the fraud detection technologies used by Kenyan insurance firms to detect fraudulent insurance claims and to establish the factors that influence the choice of the technologies. The section also outlines the fraud detection Technologies used in the insurance industry and will also outline the theoretical review.

2.2 Theoretical Review.

This section discusses the Rogers Innovation Diffusion theory, Technology Acceptance Model, and Fraud Diamond Theory to explain factors that influence a firm's or individual's choice of technology.

2.2.1 Rogers's Innovation Diffusion Theory

In his 1962 publication, Everett Rogers advanced this theory. He offered a thorough framework for comprehending both individual adoption and collective diffusion. The scope of Rogers' theory's understanding of the variables influencing a person's decision to adopt an innovation is its greatest strength. Rogers's Innovation Diffusion Theory (IDT) is a well-known theoretical framework that explains how new ideas, products, or technologies are adopted by people within a social system. The theory identifies five categories of adopters, namely innovators, early adopters, early majority, late majority, and laggards, based on the speed and degree of adoption (Bandura, 2001). The use of technology in detecting fraudulent claims can also be understood through the lens of Rogers's theory. The insurance industry has always been plagued with fraudulent claims, which not only cause significant financial losses but also damage the industry's reputation. To tackle this problem, insurance companies have been adopting various technologies such as artificial intelligence, machine learning, and data analytics to detect fraudulent claims.

According to Rogers's theory, innovators are the first to adopt new ideas, products, or technologies (Rogers, 1995). In the context of the insurance industry, innovators can be seen as early adopters of technology to detect fraudulent claims. These early adopters have recognized the potential benefits of technology and have started using it to gain a competitive edge. As more and more insurance companies adopt technology to detect fraudulent claims, it is expected that the early majority will follow suit. These adapters are typically more risk-

averse than innovators and early adopters are more likely to adopt new ideas or technologies once they have been proven effective by the early adopters.

The use of technology in detecting fraudulent claims can also help insurance companies overcome the resistance of the late majority and laggards, who are typically more skeptical about new ideas or technologies. By demonstrating the effectiveness of technology in detecting fraudulent claims, insurance companies can convince these adopters to embrace technology and improve their fraud detection capabilities.

Several studies have investigated the use of technology in detecting insurance fraud, and most of them have applied IDT as a theoretical framework. For instance, in a study by Gupta et al. (2020), the authors used IDT to examine the adoption of blockchain technology in insurance fraud detection. The study found that the relative advantage of blockchain technology, such as its ability to enhance transparency and security, positively influenced its adoption. Similarly, a study by Zhang et al. (2021) used IDT to investigate the adoption of AI-based fraud detection systems in the insurance industry, the study found that the perceived compatibility of AI technology with existing fraud detection systems, as well as its perceived relative advantage in terms of efficiency and accuracy, positively influenced its adoption. In contrast, a study by Arfi et al. (2021) examined the adoption of IoT technology in insurance fraud detection using IDT and found that the perceived complexity of IoT negatively affected its adoption, while the perceived relative advantage and compatibility positively influenced adoption. When it comes to the adoption of robotic process automation, Filgueiras et al. (2022) investigated the adoption of the technology in insurance fraud detection using IDT. The study found that the perceived relative advantage, compatibility, and trialability of RPA positively influenced its adoption, while the perceived complexity negatively affected its adoption.

The application of IDT in the context of insurance fraud detection using technology such as blockchain, AI, predictive analytics, IoT, and RPA has been useful in understanding the factors that influence the adoption of these technologies. However, there is a need for more empirical studies that explore the adoption of these technologies in the insurance industry, especially in the context of fraud detection. Furthermore, future research could investigate the interplay between different technologies and how they could be combined to enhance fraud detection in the insurance industry. The major significant strength of the IDT is its applicability across different fields and is thus useful in understanding the behavioral factors and firm features that determine the diffusion of technologies.

In this study, the IDT theory is useful in understanding the firm-level factors that determine the implementation and adoption of insurance fraud detection technologies. The insurance company can thus assess the critical factors that are likely to influence their desire to adopt fraud detection technologies and make necessary interventions. The theory is also useful in understanding the strength and weaknesses of each of the insurance detection technologies and thus informing their selection and usage. However, the IDT does not take into account of the individual resources or social support that facilitate the diffusion of innovation. This limitation is cured by the application of the Technology Acceptance Model. The Technology Acceptance Model Considers the external and social elements that the adoption of a technological concept, business idea, or innovation.

2.2.2 Technology Acceptance Model

Fred Davis advanced the Technology Acceptance Model (TAM) in 1986. The model is designed to simulate people's acceptance of technology or information systems. He utilized the notion to describe how people use computers. In Davis' (1989) TAM, the researcher sought to identify common factors influencing computer adoption that might be used to explain user behavior across various end-user computing systems and user groups. Perceived Usefulness (P.U.) and Perceived Ease of Use (PEU) are two specific beliefs that the TAM model tested. Perceived Usefulness is defined as the potential user's subjective likelihood that using a particular system (such as A.I., ML, or Blockchain) will optimize the firm's operations, whereas Perceived Ease of Use refers to the degree to which the potential user expects the target (Davis, 1986)

The use of fraud detection technologies to detect fraudulent claims can be understood through the lens of the TAM. Insurance companies have been adopting various technologies such as artificial intelligence, machine learning, and data analytics to detect fraudulent claims (Gill et al., 2005). These technologies promise to improve the accuracy and efficiency of fraud detection, but their effectiveness ultimately depends on whether users accept and use them.

According to the TAM, perceived usefulness and perceived ease of use are the two main factors that influence user acceptance of technology. In the context of fraud detection, insurance company employees are the primary users of fraud detection technologies. These employees may include claims adjusters, fraud investigators, and underwriters, among others. Perceived usefulness is particularly relevant to insurance company employees who use fraud detection technologies to detect fraudulent claims (Gill et al., 2005). Employees may be more likely to

accept and use fraud detection technologies if they believe that it will help them detect fraud more accurately and efficiently than traditional methods. For example, if employees believe that fraud detection technologies can analyze large amounts of data more quickly and accurately than manual methods, they may be more likely to use them. Regarding the perceived ease of use as a factor in the acceptance of fraud detection technologies by insurance company employees, they may be less likely to use fraud detection technologies if they find it difficult to use or understand. Therefore, insurance companies should ensure that the technology is easy to use and user-friendly.

Additionally, Venkatesh (2000) introduced the TAM 2 model, which included more thorough justifications for why users thought a particular system was helpful at three (3) different times: before implementation, one month after implementation, and three months after implementation. According to the hypothesis, users' judgments of the system's effectiveness are based on their mental assessments of how significant workplace goals and the results of doing job activities utilizing the system match up (Venkatesh & Davis, 2000).

Finally, Venkates et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) that promotes performance expectancy, effort expectancy, social influence, and facilitating factors as indicators of user behavior intention. UTAUT suggests five variables that affect a person's technology preference. They are perceived utility, extrinsic motivation, work compatibility, comparative advantage, and technology outcome expectations. In the insurance industry, the technology will be accepted if it enables the insurance firm to analyze, and sort the insurance claims, flag out anomalies, and increase the efficiency of paying honest insurance claims. Insurance firms will also choose a set of technology if it will increase their performance and enhance profit making. Further, the firms will accept the technology if the cost of acquisition and implementation is favorable and manageable. Operation requirement also plays a significant role in choosing the technology to adopt, as firms must choose the technology, they have expertise.

The TAM model is applicable in this study as it elaborates that usefulness and ease of use are key drivers to the adoption of a technological innovation or business concept by a company. Insurance detection technologies are deemed useful in reducing rising insurance fraud. The benefits that will be derived from adopting fraud detection technologies include reduced fraudulent claims and an increase in revenue for the company. Thus, the TAM is useful in

evaluating the desirability of the insurance company to implement the insurance fraud detection technologies based on the benefits to be derived from it.

2.2.3 Fraud Diamond Theory.

Detecting insurance fraud is a complex process that requires a thorough understanding of the fraudster's motives, opportunities, and rationalization. The Fraud Diamond Theory provides a useful framework for understanding the various factors that contribute to insurance fraud. The Fraud Diamond Theory is a theoretical framework developed by David T. Wolfe and Dana R. Hermanson in 2004 (Wolfe & Hermanson, 2004). The theory proposes that four key factors contribute to fraudulent behavior: opportunity, rationalization, pressure, and capability. Opportunity refers to the ease with which an individual can commit fraud, while rationalization refers to the thought process that allows an individual to justify fraudulent behavior. Pressure refers to the financial or personal pressures that drive an individual to commit fraud, while capability refers to the skills and resources required to successfully commit fraud.

The Fraud Diamond Theory has been widely used in the insurance industry to understand and prevent fraudulent claims. For example, Hu, Wang, and Wang (2017) used the Fraud Diamond Theory to analyze fraudulent insurance claims in China. They found that opportunity, rationalization, and capability were the most significant factors contributing to fraudulent behavior.

In their study, Wolfe and Hermanson (2004) stated that while perceived pressure or incentive, opportunity, and justification for committing fraud might all exist, fraud is unlikely to happen unless the fourth element of capacity is present. Anyone who might perpetrate insurance fraud must possess the necessary abilities, knowledge, and skills. In insurance, it implies that the perpetrator, either the insurer or the insured, can only commit fraud if they have the ability and skills required to commit the fraud by either presenting a fraudulent claim or faking an accident to be indemnified by the insurance company.

The capability attached to the perpetrator can be position and adequate knowledge; the position one occupies in the organization can make it easy for him/her to defraud the organization. Further, without adequate knowledge of a subject matter, one may be unable to defraud an insurance firm successfully. According to Dorminey (2010), it is the opportunity that opens doors to deception, pressure, and rationalization, bringing perpetrators closer to the door, but the perpetrators must have the capability to recognize the existence of the opportunity to walk through and commit the fraud.

The diamond theory also altered the fraud triangle's pressure component. Dorminey et al. (2012) assert that the pressure in the fraud triangle does not always correspond to external financial pressure. For example, in insurance fraud, the fraud involves more than one person; perhaps not all parties involved may have the financial motivation to submit or pay a fraudulent claim. Influential and wealthy people in the community are also perpetrators of fraud (Ramamoorti, 2009).

Dorminey (2010) and Kranacher (2011) argued that situational pressure could motivate one to commit fraud, and factors like money, ideology, coercion, and entitlement can explain that. When someone is under financial hardship, they are more likely to commit fraud. Financial strain can be brought on by debt and pressing personal and family requirements, which is consistent with the findings of (Cressey, 1950).

Insurance fraud can be easily detected and prevented if fraudsters' motivations are known and understood, potential fraudsters are predicted, and fraud targets are identified. It will be simple for insurance companies to identify factions likely to commit fraud against them by mapping and conducting thorough market research and evaluation. Insurance companies will also find it easier to know whom to watch out for and what systems or technologies to develop to find and stop fraudulent insurance claims.

2.3 Empirical Review

This section presents an empirical inquiry into past studies on the subject matter of the study. The sections present the conceptualization of fraudulent insurance claims, fraud detection and prevention, insurance fraud detection technologies and insurance firm feature that influence the adoption and implementation of insurance fraud detection technologies. The critique of the studies was undertaken to reveal research gaps.

2.3.1 Fraudulent Insurance Claims.

A purposeful act of getting money or value from an insurer under pretenses or major misrepresentations is illegal and is considered fraud if it can be proven beyond a reasonable doubt (Derrig, 2002). In contrast, Gill et al. (2005) described insurance fraud as "knowingly making a fraudulent claim, inflating a claim or adding more items to a claim, or being in any way dishonest with the objective of gaining more than legitimate entitlement." The term "insurance fraud" refers to fraudulent policyholders who commit insurance fraud.

An illegitimate or illegal scheme intended to provide financial gain for oneself is called a fraudulent claim. A false claim is one in which the claimant purposefully omits, misrepresents,

modifies, or conceals material facts about the claim with the intention and hope of receiving reimbursement from the policy to which they would not otherwise be eligible (Derrig, 2002).

According to the National Association of Insurance Commissioners (NAIC), there are two main classes of insurance fraud, hard and soft. Hard fraud happens when someone purposely invents a loss, such as firing a house, intentional accident, or even faking death. On the other hand, soft fraud is a more common type of insurance fraud involving embellishing the situation to obtain more profit from the agreement. A good example is a person who misrepresents his health conditions to obtain a good health policy or tries to fix all damaged parts of the car after a minor accident happens.

Table 1.1: Nature of fraudulent insurance claims

Type of Insurance	**Fraud**
Auto.	False or exaggerated theft repair claims, staged accidents, fabricating the timing or details of an accident to obtain coverage, false stolen-car reports from the owner, and "Jump in" (someone not in the vehicle at the time of the accident).
Homeowner.	False or exaggerated claims of property damage, burglary or theft, arson, and purposeful damage claim.
Health/Medical Insurance Fraud	Billing for services not delivered, charging for services that were more expensive than what was delivered, charging for unnecessary services while claiming that they were necessary, double billing, setting up "ghost hospitals," and using someone else's insurance to pay for services are all examples of billing fraud.
Workers' Compensation	An absence of workers' compensation insurance by the employer, making false claims of workplace injuries, misclassifying employees' jobs on purpose, working while receiving benefits from workers' compensation, and fabricating injuries are all examples.

Source: IRA, 2022

2.3.2 Fraud Detection and Prevention.

Fraud detection involves a series of procedures used to prevent the acquisition of property or money under pretenses. Techniques for preventing fraud help identify fraud before it happens. To avoid fraud, one must first have a thorough understanding of it, including knowledge of its causes, consequences, methods of commission, and methods of prevention. Fraud prevention and detection are closely related. Fraud can be found and reported to the proper authority with the aid of detection techniques.

Previous research found that weak internal control and inadequate corporate governance enhance the likelihood of fraud. Within the company, corporate managers are generally in charge of fraud detection and prevention (PwC, 2008). According to Kadar (2017), fraud detection involves a series of procedures and methods used to spot, track down, and stop fraud. Fraud, swindles, and bad actors hurt the online business world in several ways. Businesses must act to ensure that fraud is found and stopped before it impacts operations.

The first step is determining where the risk of fraud is at, after that, businesses or individuals can choose whether to manually use fraud detection software tools and techniques or automatically detect it. Fraudulent claims can involve fabricating losses as well as making flimsy loss claims (Tennyson, 2008). Fraud may also be the result of planning or opportunism. Premeditation refers to a circumstance in which a person obtains protection with the initial intent to commit fraud but acts opportunistically and commits an act with the primary purpose of obtaining insurance coverage need not be fraud, but fraud is committed once an opportunity or situation arises (Tennyson, 2008).

2.3.3 Fraud Detection Technologies Used in Insurance Industry.

2.3.3.1 Blockchain in Insurance.

A blockchain data format makes it possible to create a digital log of transactions and share it among a distributed network of computers (Munich American Reassurance, 2020). The decentralized nature of blockchain technology has the potential to reduce fraudulent activities by providing a secure and transparent platform. According to Zheng et al. (2018), blockchain technology can help in preventing fraud by allowing insurers to access a shared database of claims data, which reduces the possibility of duplicate or false claims. The study by Lo and Wang (2019) highlighted that blockchain technology could improve the efficiency of fraud detection by reducing the time required to verify claims and providing a more transparent process.

In his study on Blockchain-based solutions for combating healthcare insurance fraud, Liu (2019) suggests a Blockchain-based healthcare insurance anti-fraud service. His research demonstrated that using a blockchain-based system could be more effective in addressing difficulties with healthcare insurance anti-fraud, including falsified data, hiding third-party responsibility accident fraud, erroneous electronic bill reimbursement, and others.

A study by Zheng et al. (2019) proposed a blockchain-based approach for detecting fraudulent health insurance claims. The authors used smart contracts and distributed ledger technology to ensure the transparency and traceability of health insurance transactions, which helped to detect and prevent fraudulent claims. The study showed that blockchain technology can significantly reduce the cost of detecting and preventing fraud. Another study by Seebacher et al. (2020) proposed a blockchain-based approach for detecting fraudulent car insurance claims. The authors used blockchain technology to create a tamper-proof and immutable database that stores all the relevant information related to car insurance claims. The study showed that blockchain technology can help to identify patterns and anomalies in car insurance claims, which can help insurance companies to detect fraudulent claims.

Some studies have raised concerns about the use of blockchain technology in detecting fraudulent insurance claims. A study by Mooney et al. (2018) argued that blockchain technology alone cannot solve the problem of fraudulent insurance claims. The authors suggested that a combination of blockchain technology and artificial intelligence (AI) can be more effective in detecting fraudulent claims. The study also highlighted the importance of having a comprehensive and integrated approach to fraud detection. Moreover, a study by Banerjee et al. (2019) highlighted the lack of awareness and understanding of blockchain technology among insurance professionals as a significant barrier to its adoption. The study also highlighted the need for regulatory clarity and standardization to facilitate the adoption of blockchain technology in the insurance industry. According to Szymanska et al. (2020), the implementation of blockchain technology in the insurance industry is still in its early stages, and several challenges need to be addressed. Some of these challenges include regulatory compliance, interoperability, scalability, and data privacy concerns.

Hiererra, et al. (2022) conducted a study on Blockchain technology for Fraud Detection and Risk Prevention in Insurance Industry. The research method uses a qualitative approach through observation of the mechanisms and business processes in insurance companies,

especially those related to the claim process, to identify existing problems. The result of this research is a blockchain model to reduce fraud and risk for the insurance industry in general.

Roriz and Pereira (2019) conducted a study on the use of blockchain-based solutions for the motor vehicle sector. The study aimed to discuss how blockchain and smart contracts may be used together to improve organizational operations. It was established that blockchain technologies in the form of smart contracts are effective in detecting fraud claims in the insurance industry.

2.3.3.2 Artificial Intelligence.

The Oxford Dictionary defines A.I. as the theory and creation of computer systems capable of carrying out tasks that would typically require human intelligence, such as speech recognition, visual perception, decision-making, and language translation. Artificial intelligence (AI) and predictive analytics have been widely used in fraud detection within the insurance industry. AI algorithms can analyze large amounts of data to identify patterns that indicate potentially fraudulent activities. According to Li et al. (2018), AI algorithms can be used to detect fraudulent claims by analyzing the claimant's behavior patterns, such as claim frequency, location, and history.

Chummun (2018) discovered that the integration of AI systems in the low-income insurance market could enhance the sustainable success of this niche market. The low-income market is characterized by low premium revenues and high transaction costs, making it a challenging and uncertain profit business. The study focused on how A.I. can reduce fraud in the inclusive cover niche in developing African countries. The study also discovered that A.I. could help insurers with individual claims by investigating the alleged incidents. The researcher provided a tragic accident involving the death of a driver and claimed that it was raining at the time of the incident. If this is the case, A.I. can verify weather reports. The system can flag a claim as requiring further investigation if the A.I. searches reveal that the policyholder's claimed circumstances may not have occurred as claimed.

The study also discovered that insurers could use artificial intelligence to identify patterns of insurance fraud in claims. Using self-learning software that processes "big data" (extremely large amounts of data from various sources that can be "mined" to provide information on patterns and trends), artificial intelligence (A.I.) can identify these patterns and flag claims that are thought to warrant further investigation.

Sharma and Bokoro (2020) proposed a blockchain and AI-based secure and intelligent system to detect health insurance fraud in their study on Blockchain and AI-empowered Healthcare Insurance Fraud Detection. They also concluded that many problems with health insurance claims (HICs), including security, privacy, and data interoperability, were resolved by combining Blockchain and ML for HIC fraud detection. Insurance subscribers can give their consent to share their records with the parties involved in HIC using blockchain, which offers secure HIC data storage and tamper-proof HIC data transfer.

Chummun (2018) argued that since neural networks and rules-based systems can flag relationships between claimants, doctors, lawyers, and other stakeholders, as well as any other events linked to fraud, the insurance industry can use A.I. to detect fraud during the claims processing phases. After learning the characteristics of fraudulent claims, the network can quickly spot potential fraud in new claims. Insurers can use A.I. to spot patterns of insurance fraud in claims. Self-learning software that processes "big data" can identify these patterns to flag assertions that need further inquiry.

Amerirad et al. (2023) conducted a study on adversarial Artificial intelligence in insurance. The paper was designed to review adversarial AI and discuss its implications for the insurance sector. The study found that AI algorithms are effective in detecting fraud claims in the insurance sector.

Aslam, et al. (2022) conducted a study on the use of artificial intelligence and machine learning for Insurance fraud detection. The results reveal that the support vector machine outperforms in terms of accuracy, and the logistic regression achieves the highest f-measure score. The findings of this study are beneficial for fraud detection in the auto insurance industry.

2.3.3.3 Internet of Things (IoT).

According to Oracle Kenya, IoT is a network of physical items, or "things," that are connected to and exchange data with other systems and devices through the internet. These "things" are integrated with sensors, software, and other technologies. Several studies have investigated the use of IoT technology by insurance companies in detecting fraudulent insurance claims. For instance, Fu et al. (2019) explored the use of IoT technology in the insurance industry and found that IoT devices such as sensors, wearables, and telematics could be used to collect data on the insured item, such as a car, property, or a person. The data collected by these devices could be analyzed to detect anomalies that indicate potential fraud.

Similarly, Singh and Tripathi (2021) conducted a study on the use of IoT technology in the insurance industry and found that IoT devices such as smart home devices and connected cars could be used to collect data on insured property. The data collected could be analyzed using machine learning algorithms to detect potential fraud. In another study, Sarrica and colleagues (2018) examined how IoT technology could be utilized in the insurance sector. Their research discovered that IoT devices, such as smart home devices, connected vehicles, and wearable technology, can gather information on both the insured individual and their property. The data collected from these devices could be scrutinized to identify any possible instances of fraud, such as deceitful injury claims.

However, despite the potential benefits of using IoT technology in detecting fraudulent insurance claims, several challenges need to be addressed. For instance, Singh and Tripathi (2021) found that the use of IoT devices in the insurance industry raised concerns about privacy and security. Moreover, the cost of implementing IoT technology could be a barrier for some insurance companies.

Sahni, et al. (2020) studied insurance fraud identification using computer vision and IoT. The proposed work is an amalgam of computer vision, deep learning, and the Internet of Things and aims to inculcate the positives of each of these technologies. The results display that an amalgam of computer vision, deep learning, and the Internet of Things combined has an accuracy of 97% in detecting fraudulent insurance claims in the insurance industry.

2.3.3.4 Machine Learning (ML).

SAS states that machine learning is a data analysis technique that automates the building of analytical models. It is a type of artificial intelligence where machines learn from data, recognize patterns, and make decisions with limited or no human involvement. Machine learning (ML) has also been widely used in fraud detection within the insurance industry. ML algorithms can analyze large amounts of data to identify potentially fraudulent activities by identifying patterns and anomalies in data (Wang and Ma, 2020). The study by Choudhary et al. (2019) highlighted that ML algorithms could improve the accuracy of fraud detection by identifying complex patterns and anomalies that may be difficult to identify manually.

Several studies have demonstrated the potential of ML technology in detecting fraudulent insurance claims. For instance, a study by Kim et al. (2019) used an ML algorithm to analyze insurance claims data and identified fraudulent claims with a high degree of accuracy.

Similarly, a study by Zhong et al. (2021) utilized an ML-based approach to detect fraudulent auto insurance claims and reported promising results.

While the use of ML technology has shown great potential in detecting fraudulent insurance claims, some scholars have raised concerns about its effectiveness in practice. For example, a study by Bolat et al. (2020) reported that the accuracy of ML algorithms can be limited by the quality and completeness of the data used in training them. In addition, the study highlighted the potential ethical issues associated with the use of ML algorithms in the insurance industry, such as the potential for algorithmic bias and discrimination.

Additionally, several research studies have suggested that machine learning (ML) technology should not be the sole means of detecting fraudulent insurance claims. Instead, it should be used in conjunction with traditional methods, including expert analysis and investigation. For example, a recent study conducted by Freitas and colleagues (2021) recommended that ML algorithms be utilized as an additional tool to traditional fraud detection techniques rather than a substitute. While the use of ML technology in detecting fraudulent insurance claims shows promise, it is not without limitations and potential ethical issues. Therefore, further research is needed to address these concerns and explore the optimal combination of ML technology and traditional methods in detecting fraudulent insurance claims.

Tian (2017) conducted a study on insurance fraud detection using a data mining approach. Compared with the traditional way to solve the fraud problem, Data Mining technologies and models (algorithms) can help people in the insurance industry to figure out questionable cases effectively, improve the efficiency of risk management greatly, and to reduce unnecessary costs massively. The study found Data Mining technologies to be accurate in detecting fraud.

Li, et al. (2023) conducted a study on Motor Vehicle Insurance Anti-Fraud Modeling Based on a Stochastic Differential Game System. The study explored the supervision of motor vehicle insurance fraud from the perspective of a tripartite game. it was found that the game with government supervision is more conducive to reducing the insured's fraud intensity, and the simulation proves the impact of different parameters on system stability. However, the study focused on motor insurance fraud claim detection in China contrasting the current study that focuses on Kenya presenting a contextual gap.

2.3.3.5 Robotic Process Automation.

According to UI-path, robotic process automation (RPA) is a software technology that makes it easier to create, deploy, and administer software robots that mimic how people interact with digital systems and software. Software robots, like humans, can interpret what is displayed on the screen, use the proper keystrokes, navigate computer systems, locate and extract information, and carry out a variety of predefined operations. Robotic Process Automation has gained significant attention in recent years as a promising technology for detecting fraudulent insurance claims. Several studies have investigated the use of RPA in the insurance industry, and this literature review aims to critically evaluate their findings.

One study by Liao et al. (2020) conducted a systematic review of RPA in insurance, which included 26 articles. They found that RPA can improve efficiency, reduce costs, and enhance customer experience in the insurance industry. However, the study did not specifically focus on fraudulent claims detection.

In contrast, another study by Jha et al. (2020) specifically examined the use of RPA for fraud detection in insurance. They highlighted the potential benefits of RPA, such as real-time monitoring, automatic claim validation, and fraud prediction. However, the study also noted that RPA implementation can be challenging and require significant resources.

Similarly, a study by Gupta et al. (2020) investigated the use of RPA for fraud detection in the Indian insurance industry. They reported that RPA can reduce fraudulent claims by 20-30% and improve processing time by 50-70%. However, the study also acknowledged the need for a robust governance framework to ensure the ethical use of RPA.

According to Cranfield & White (2016), ten automated processes were implemented within the insurance industry in less than two years, which resulted in a reduction in the processing time of over 90% and uninterrupted operations with multi-skilled robots working on processes 24 hours a day, seven days a week. Automation freed up resources so they could focus on tasks that benefited customers. The absence of human mistakes in the process has been a significant additional benefit. On the other hand, a study by Kaminska-Labbé and Ouvrard (2019) argued that RPA is not a silver bullet for fraud detection in insurance. They suggested that RPA should be used in conjunction with other technologies and human expertise to achieve optimal results. The study also emphasized the importance of data quality and the need for ongoing monitoring and evaluation of RPA systems.

2.3.4 Insurance Firms Characteristics.

The sections review various Insurance Firms Characteristics that are likely to influence the adoption and implementation of fraud detection technologies. The Insurance Firms Characteristics investigated included the profitability, size of the insurance firm, insurance products, and corporate governance characteristics.

2.3.4.1 Profitability.

Profitability is a measurement of a company's earnings in relation to its expenditures (Gartner, 2022). More effective businesses will make more money relative to their costs than less effective businesses, which must spend more to make the same amount of money.

High operation costs are one of the main reasons why most insurance companies fail to meet their profit targets. In addition, most insurance companies are on a losing streak due to increased fraud. Copeland (2022) claims that fraud and high management costs reduce insurance companies' bottom lines.

For an insurance company to profit, its Gross Written Premium must be higher than its administrative costs and payouts. Administration costs and commissions paid to middlemen are included in the cost of running an insurance company, while "claims" are the formal requests policyholders make to their insurer for compensation for losses covered by the policy. The growth of the insurance industry in the country is hindered, according to reports from industry players, because of the prevalence of unchecked fraud. An individual may submit a claim for Sh3 billion, but an assessment may reveal that only Sh500 million is owed (Lamtey, 2022). Because of this, profits could be reduced if employees are not vigilant enough.

A.I.'s value to the insurance sector extends far beyond its use in combating fraud. The sector is reportedly on the verge of a technologically-driven paradigm shift (Amaresh, 2022). With the help of A.I., the insurance industry may enhance profitability by as much as 40% by 2030, all while lowering operational costs by the same percentage. A.I. will also improve employee output, customer service, and business stability. According to Amaresh (2022), the world is evolving, and soon things like driverless automobiles, smart homes, and personal space travel will be commonplace. To maintain a competitive advantage and continue operations far into the future, insurance companies will need to react to these developments by gradually integrating A.I. into their operations.

Business spending on artificial intelligence (A.I.) enabled financial fraud detection, and prevention strategy platforms are expected to rise from a little over $6.5 billion in 2022 to more than $10 billion in 2027 (Walker, 2022). He argues that as fraudsters increase the sophistication

of their attacks, legitimate businesses and insurers will become more proficient in using cutting-edge AI-enabled fraud detection tools to address the growing threat. There is a growing need for better fraud prevention services, and A.I.'s capacity to identify fraudulent payment patterns at scale is essential to this. Financial savings from using A.I. are expected to be essential for expanding system utilization beyond regulatory compliance (Walker, 2022). Offering real ROI on fraud protection services through a positive feedback loop of increasing model accuracy and data availability, from $2.75 billion in 2022, he expects cost savings to rise 285% to $10.4 billion worldwide by 2027.

Agwor (2017) studied fraud prevention and business performance in quoted manufacturing companies in Nigeria. Primary and secondary data were collected from the manufacturing companies. The study found that the influence of fraud prevention is more positive and very significant on business profitability, than on effectiveness and business efficiency, which appears to have weak influence in the quoted manufacturing companies in Nigeria. However, the study did not show whether profitability influence the desire of the company to adopt fraud detection technologies.

2.3.4.2 Size of the Insurance Firm

Like the adoption of any new technology, the size of an insurance company significantly impacts which fraud detection methods it chooses to implement. There are four reasons to believe that a company's size and market share have a beneficial effect on its innovativeness and adoption of new ideas, as suggested by research published in 2009 by Surinach et al. first, larger companies are more likely to engage in external innovation due to a combination of increased appropriability and greater access to capital. Market-leading companies are more inclined to embrace new technologies because they are better positioned to reap the benefits of doing so. Secondly, bigger and more profitable enterprises are more likely to have the monetary resources necessary for procuring and installing a new technology even amid inefficient capital markets. Thirdly, companies with a larger part of the market can often better distribute the risks associated with new initiatives since they have more options when it comes to which technologies to implement and can test out new ones without having to shut down their existing ones. Finally, large enterprises are often the first to adopt new technologies because of economies of scale in production and the ability to spread the various fixed costs involved with adoption across a larger number of units.

While studying the impact of firm size on innovation and technology adoption (Kijkasiwat & Phuensane, 2020), the authors stated that access to capital is a key factor in the creative process. The authors contended that internal funding constraints impede the innovative capabilities of small and medium-sized businesses. If a large company experiences a drop in internal financing, it may easily receive replacement capital from external formal financial institutions; therefore, this does not cause a drop in inventive performance. However, cash flow declines are more likely to occur in SMEs that struggle to raise funds internally. Then, they have a harder time getting traditional bank loans and other institutional financings. Larger insurance firms have access to adequate internal finances as well as external funding to deploy and maintain sophisticated fraud detection technologies, unlike their small and medium counterparts.

The findings of Kijkasiwat and Phuensane (2020) are supported by Nguyen et al. (2022), who suggest that larger firms usually have sufficient resources to try out new technologies and have more capabilities to bear the risks and expenses of implementing innovations. Conversely, small enterprises with few resources are more prone to choose a short-term or passive viewpoint towards innovations and technological adoptions, making them more susceptible to external context changes.

2.3.4.3 Insurance Products in Kenya.

The idea of insurance is straightforward but sometimes misunderstood. According to Segodi and Sibindi (2022), insurance serves as a financial safety net that aids people in recovering after unfavorable events like fires, theft, lawsuits, or vehicle accidents. An insurance policy, which is a binding legal agreement between a person and their insurance provider, is what people get when they buy insurance. Insurance pays the insured or a chosen recipient, known as a beneficiary, per the policy's provisions when the insured experiences a loss covered by their policy and files a claim. According to the Association of Kenya Insurers 2022, there are two broad categories of insurance products in Kenya. The first category of insurance is known as General or Non-life insurance, which encompasses any insurance that is not classified as life insurance. There are approximately 14 types of insurance within this category, but the most common ones include Motor Private/Commercial Insurance, which covers the loss or damage to a vehicle and any legal liabilities related to third-party death, injury, or property damage caused by its use. Another popular type of general insurance is Home (Fire Domestic) Insurance, which protects a house and its contents from risks such as fire, theft, extreme

weather damage, and other losses. It may also include coverage for domestic workers, occupiers, and owners' liabilities. Lastly, Medical Insurance, which covers the medical expenses of the policyholder and their dependents, is a frequently seen type of general insurance. The typical coverage includes out-patient and in-patient treatments, along with dental and optical coverage.

However, despite the clear importance of insurance premiums, most Kenyans are still reluctant to get insurance. Although there are various reasons behind this reluctance, most experts believe it is due to the higher premiums and rampant fraud in the insurance sector. The issue of insurance penetration remains a key concern for insurance practitioners, scholars, and policymakers. Despite the social, economic, and political transformations the country has seen over the past ten years, insurance penetration in Kenya has remained low, at 3.1% of GDP as of August 2012 (Kamau, 2013). The Association of Kenya Insurers commissioned a significant study in 2013 to determine the true prevalence of health insurance fraud. A total of 1,000 persons were surveyed, including beneficiaries, medical professionals, insurance firms, and connected business staff members. It was discovered that 28% of respondents had received strange insurance claims throughout the previous year, and 21% had seen fraudulent claims (AKI, 2013). This partly explains the rising uptake of fraud detection technologies by insurance firms to reduce losses and improve the public's faith in insurance coverage. According to IRA (2022), insurance products in the Kenyan market include, and not limited to, Auto insurance, General Insurance, Medical insurance, life insurance, fire insurance, and aviation insurance.

2.3.4.4 Corporate Governance Characteristics

The prevention and detection of fraud within insurance firms is primarily the responsibility of the management under the oversight of those charged with governance. Auditors, along with other members of the corporate governance and reporting ecosystem, also have an important role. Although the adoption of fraud detection technologies is tipped to reduce the cases of fraudulent insurance claims, there are many factors involved in the adoption of such technologies. Indeed, technology is not a panacea and the human element also comes into play (Persico, 2019). There is an opportunity for all involved – including management and boards, auditors and regulators – to focus more on corporate culture and behaviors to support fraud detection.

The complexity and frequency of fraudulent insurance claims increased as a result of increased internet usage and the emergence of a more tech-savvy generation. Additionally, it may require

more than a standard audit to uncover the evidence when a fraud involves a large network of management and outside parties (Persico, 2019). This issue affects a lot more than just the auditing industry. Large-scale fraud is typically well-planned and challenging to spot. Although auditing is a crucial check, it is not the only measure. A "three lines of Défense" strategy against fraud, consisting of corporate governance, the auditor, and capital markets monitoring, is helpful in this situation.

Since the board of directors is a key component of corporate governance, it is obvious that its makeup must be responsive to the fundamental duties that are delegated to it, including monitoring and supervising, preventing opportunistic executive behavior, and giving advice to decision-makers to enhance the management of the company (Martin and Herrero, 2018). The implication is that, in contrast to companies with smaller and less diverse boards of directors, insurance firms with larger and more diverse boards benefit from a wealth of knowledge that can be crucial in helping decision-makers select cutting-edge technologies that can reduce fraudulent insurance claims.

Odhiambo (2016) evaluated of fraud management strategies adopted by insurance companies in Kenya. A survey was conducted among 25 of the 50 insurance companies to establish specific fraud management strategies in use and evaluate their effectiveness. The study established that insurance companies use normal internal control systems such as internal and external audit functions, underwriting, claims management, IT, and management committees to manage fraud.

Birol (2019) studied corporate governance and fraud detection in Borsa Istanbul. 134 companies listed on Istanbul Stock Exchange have been studied via benefiting their financial statements published between 2010 and 2014, and their corporate governance applications announced. Findings show that corporate governance principles and their applications in Turkey have not made the expected effect on fraud risk yet. On the other hand, profitability has an impact on the risk of preparing fraudulent financial statements and gives clues about misstatements, consistent with the literature.

Halbouni, Obeid, and Garbou (2016) Corporate governance and information technology in fraud prevention and detection: Evidence from the UAE. This study used a survey of financial accountants and internal and external auditors to assess their perceptions of the effectiveness of IT and corporate governance. The results indicate that corporate governance has a moderate

role in preventing and detecting fraud in the UAE and that IT has the same role as traditional fraud prevention and detection techniques.

2.4 Research Gap.

Existing research on the utilization of technology in the insurance sector for the detection of fraudulent insurance claims shows that the use of technology in insurance sector has helped to improve the performance of insurance firms in terms of financial performance and fraud detection and prevention. The researches has shown how crucial the fraud detection technologies are to the insurance sector. Therefore, there is a knowledge gap regarding the current technologies employed by Kenyan insurance companies, the variables influencing the adoption and implementation of technology and the insurance companies' perceptions on the efficiency of technologies in identifying fraudulent insurance claims. The following research gaps were established after a complete review of relevant research. A study by Otiso (2017) on the effects of technology on the performance of insurance companies in Kenya concluded that increased application of technology leads to enhanced performance. A gap was bridged by the current study focusing on specific fraud detection technologies used in detecting fraud among insurance firms in Kenya. A study by Susan (2021) on the effects of technology adoption on the underwriting process among the top five insurance companies in Nairobi County concluded that digital claim processing had a positive and significant effect on the underwriting process among insurers in Nairobi County. The study presents a contextual gap since it focused only on five top insurance firms in Nairobi. Additionally, a gap in the form of fraud detection technologies used in fraudulent claims detection is presented. A study by Kamande (2018) on the predictors of computerized financial fraud among commercial banks in Kenya concluded that the influence of quality management, employee behavior anomalies, and operational red flags were predictors of computerized financial fraud in commercial banks in Kenya. This study presents a contextual research gap. The current study moves past predictors of fraud to establish the specific technologies used by Kenyan insurance firms to detect fraudulent insurance claims.

A study by Gakuru (2016) that sought to establish the effects of card fraud detection techniques on the performance of commercial banks in Nairobi, Kenya, established a significant relationship between strong authentication techniques on the performance of banks. A gap is presented since this study only linked authentication techniques to good performance. This

presents a contextual research gap since it was conducted on commercial banks rather than insurance firms. The study also did not establish the fraud detection technologies used in fraud detection and prevention, which presents a good gap for the present research. Focusing on ICT utilization in commercial banks in Kenya, Ngalyuka (2013) sought to establish the relationship between ICT utilization and fraud losses in commercial in Kenya. The research concluded that ICT utilization had exposed commercial banks in Kenya to more fraud. The research further recommends more robust fraud mitigation technologies in the process of ICT adoption, this presents a research gap since the current study seeks to establish technologies used to detect and eliminate fraudulent claims by insurance firms in Kenya.

A study by Enegi et al. (2019) on electronic banking fraud, fraud detection and control concluded that integrating biometrics in electronic banking can mitigate increased banking fraud cases. This research presents a contextual gap since it was conducted in the Nigerian banking sector. The current study focuses on the specific technologies used by Kenyan insurance firms in detecting fraudulent claims. Another study by Bhasin (2016) on the role of technology in combating bank fraud concluded that banks could leverage advances in technology and analytics to improve fraud prevention and reduce fraud losses. This research presents a gap since it only analyses the role of technology without establishing the technologies that were used. The research also presents a contextual gap since it was conducted in the Malaysian banking sector, while the current research will establish the fraud detection technologies used by insurance firms in Kenya to detect and prevent fraudulent claims. Table 2.1 shows the summary of research gaps.

Table 2.1: Summary of Research Gap

Author	Place of Research	Article Title	Conclusion	Research Gap	How this study addresses the gap
(Otiso,2017)	Kenya	Effect of Technology on the Performance of Insurance Companies in Kenya	increased application of technology leads to enhanced performance	The research only focuses on technology in general and fails to incorporate the fraud detection technologies. Also, there is no focus on the technology being used to detect fraudulent insurance claims.	A gap will be bridged by the current study by focusing on specific fraud detection technologies used in detecting fraud among insurance firms in Kenya
(Ngiri,2021)	Nairobi	Effect of Technology Adoption on Underwriting Processes among Top Five Insurance Companies in Nairobi Country.	Digital claim processing positively and significantly affected the underwriting process among insurers in Nairobi County.	The study presents a contextual gap since it focused only on five top insurance firms in Nairobi. Additionally, the study did not list the technologies insurance firms used to prevent fraudulent claims.	The proposed study will fill this gap by conducting a comprehensive assessment of fraud detection technologies used by Kenyan insurance firms in detecting and preventing in in fraudulent insurance claims. The study will cover a broader sample of insurance firms across the country

Author	Place of Research	Article Title	Conclusion	Research Gap	How this study addresses the gap
					and will examine specific fraud detection technologies used to prevent fraudulent claims to provide a more comprehensive picture of the current state of fraud prevention in the Kenyan insurance industry.
(Wairimi,2018)	Kenya	Predictors of Computerized Financial Fraud among Commercial Banks in Kenya	The influence of quality management, employee behavior anomalies, and operational red flags were predictors for in computerized financial fraud in commercial banks in Kenya	The research was conducted in the banking sector and not among Kenyan insurance firms hence a contextual gap.	The proposed study will fill this gap by specifically focusing on the Kenyan insurance industry. By focusing on the insurance sector, the study will provide a more accurate and relevant assessment of the state of fraud prevention in the

Author	Place of Research	Article Title	Conclusion	Research Gap	How this study addresses the gap
					Kenyan insurance industry.
(Gakuru,2016)	Nairobi	The effects of card fraud detection techniques on the performance of commercial banks in Nairobi, Kenya	The research established a significant relationship between strong authentication techniques on the performance of banks.	Contextual research gap since the research focused on effects and not on establishing technologies to prevent fraudulent claims. The research was also conducted in the banking and not the insurance sector.	The proposed study will fill this gap by specifically focusing on the fraud detection technologies used by Kenyan insurance firms to prevent fraudulent claims.
(Enegi et al,2019)	Nigeria	electronic banking fraud, fraud detection, and control	Integrating biometrics in electronic banking can mitigate increased banking fraud cases.	This research presents a contextual gap since it was conducted in the Nigerian banking sector.	The proposed study will fill this gap by specifically focusing on the Kenyan insurance industry. By conducting the study in Kenya, the research will provide a more relevant and accurate assessment of the fraud detection technologies used by Kenyan

Author	Place of Research	Article Title	Conclusion	Research Gap	How this study addresses the gap
					insurance firms in detecting and preventing fraudulent claims.
(Bhasin,2016)	Malaysia	Role of Technology in combat bank fraud	Banks can leverage advances in technology and analytics to improve fraud prevention and reduce fraud losses.	The research only focuses on technology in general and fails to incorporate the specific technology hence the contextual gap.	The current research will establish fraud detection technologies used by insurance firms in Kenya to detect and prevent fraudulent claims.

Source: Researcher, 2023

2.5 Conceptual Framework.

According to Miles and Huberman (1994), a conceptual framework is a diagram or written blueprint, either in narrative or graphic form that identifies key points, variables, key elements or ideas, and relationships to be considered in the study. It is a detailed description of what is said to be crucial for the research.

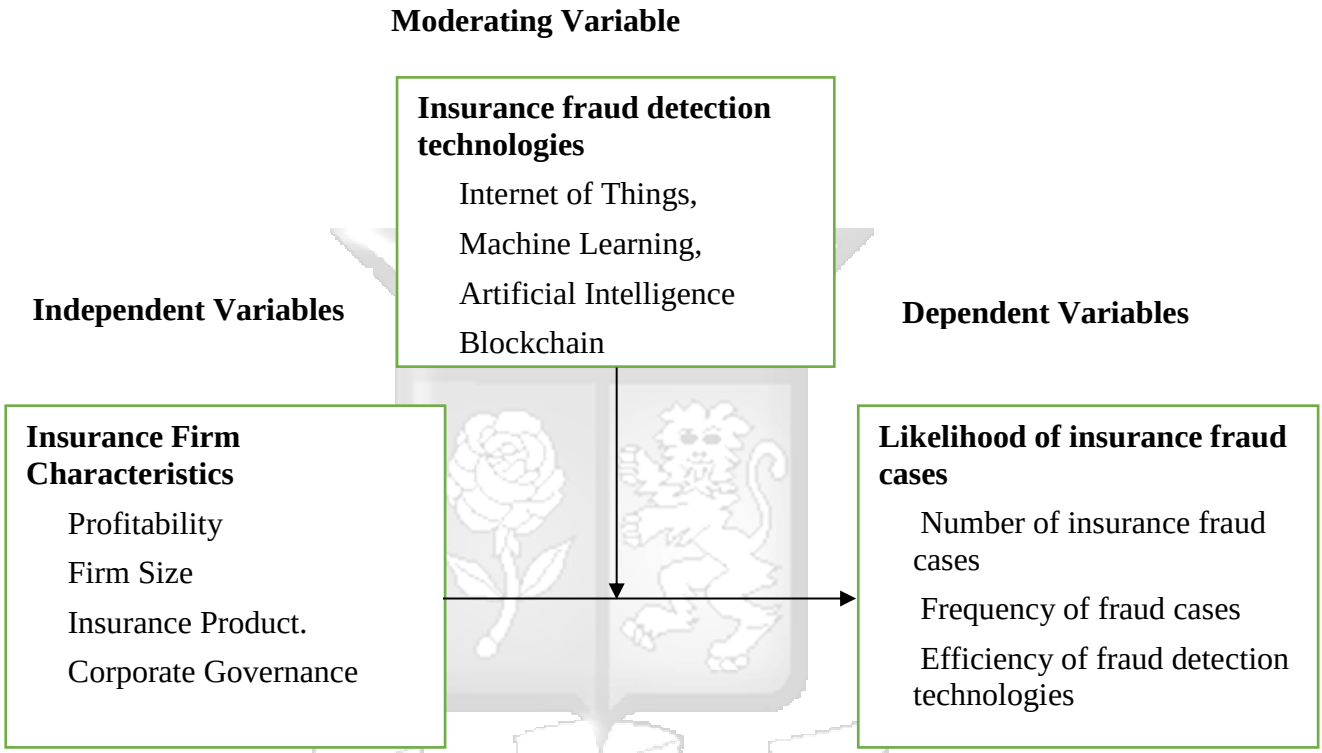

Figure 1.1: Conceptual Framework

Figure 1.1 depicts the conceptual framework of the study. The independent variable is the insurance firm characteristics that comprise profitability, firm size, insurance products, and corporate governance. It is postulated that the insurance firm characteristics include profitability, firm size, insurance products, and corporate governance have a significant effect on the likelihood of insurance fraud cases measured using a number of insurance fraud cases and frequency of fraud cases. However, to reduce cases of insurance fraud claims, the insurance companies have resorted to implementing insurance fraud detection technologies. There are several insurance fraud detection technologies, however, this study narrowed to Internet of Things, machine learning, artificial intelligence, and blockchain. The study thus postulates that the effect of insurance firm characteristics on the likelihood of insurance fraud in Kenya is moderated by the deployment of insurance fraud detection technologies

2.6 Operationalization of Variables

Table 2.2 shows how each of the variables is measured.

Table 2.2: Operationalization of Variables

Variable	Description	Measurement indicators
Detection and prevention of fraudulent insurance claims	The ability of insurance companies to identify and prevent insurance claim frauds	● Number of fraud insurance claims encountered ● Efficiency of fraud detection technologies
Insurance fraud detection technologies	refers to technological applications and innovation used to detect insurance fraud by insurance companies	● Bloch chain ● Machine Learning ● Artificial intelligence ● Internet of Things ● Robotic Process Automation
Usefulness of insurance fraud detection technologies	refers to the benefits derived from using insurance fraud detection technologies. The benefits may include reduced losses arising from false claims and rising ROI	● Reduction in claim losses ● ROI
Efficacy of fraud detection technologies	Is the reliability of the insurance fraud detection technologies to detect insurance fraud	● Accuracy ● Ease of use

2.7 Summary of the Literature Review.

This chapter provided the theories that guided the study. The theories included Rogers Innovation Diffusion theory, Technology Acceptance Model, and Fraud Diamond Theory to explain factors that influence a firm's or individual's choice of technology. In addition, an empirical review of studies conducted on fraudulent insurance claims, fraud detection and prevention, insurance fraud detection technologies and insurance firm feature that influence the adoption and implementation of insurance fraud detection technologies. The chapter also presented a summary of the research gaps and conceptual framework.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction.

This chapter outlines a comprehensive plan for the study, including the design, target population, data gathering, and examination processes.

3.2 Research Philosophy.

The research philosophy for the study was positivism. Positivism is a philosophical paradigm that emphasizes the use of scientific methods in studying and understanding social phenomena. In this study, the positivist approach allowed the researcher to collect and analyze quantitative data on the fraud detection technologies used by Kenyan insurance firms in detecting and preventing fraudulent insurance claims. This approach involved a systematic and objective investigation of the research problem, which enables the researcher to test the hypothesis and arrive at empirical findings. According to Park, et al. (2020) positivism research philosophy, allows for use of methodology that comprises selection of sample, measurements, and analysis and drawing conclusions about hypotheses.

Positivism focusses on identifying explanatory association or causal relationship through quantitative approaches. The use of positivism also ensured that the study is replicable, reliable, and generalizable to other contexts beyond the Kenyan insurance industry. Positivism research philosophy was also used by Odhiambo (2016) and Mambo (2019) in evaluating fraud management strategies adopted by insurance companies in Kenya. Similarly, Hiererra, et al. (2022) employed positivism in a study on blockchain technology for fraud detection and risk prevention in insurance industry. The Positivism research philosophy can also be used with other theoretical frameworks and models. Mwenemeru et al. (2023) employed TAM alongside positivism research philosophy while studying decision maker characteristics and adoption of IoT within Insurance Firms in Kenya. Likewise, Mazikana (2019) employed TAM alongside positivism research philosophy while studying the effect of automating customs systems on performance of Zimbabwe Revenue Authority.

3.3 Research Design.

The research design being used in this study is a descriptive cross-sectional survey, which is aimed at assessing the fraud detection technologies used by Kenyan insurance firms in detecting and preventing fraudulent insurance claims. According to Asenahabi (2019), a descriptive cross-sectional survey is a research design that collects data from a sample of

participants at a single point in time to describe a particular phenomenon. In this case, the phenomenon being studied is the use of fraud detection technologies by Kenyan insurance firms in detecting and preventing fraudulent claims.

In a cross-sectional study, the investigator measures the outcome and the exposures in the study participants at the same time. The research design enabled the collection of data on the adoption and use of technology to identify fraudulent insurance claims in the insurance industry. By using a cross-sectional design, the results from each of the 56 insurance companies can be uniformly analyzed, providing insights into the prevalence of fraud detection technologies use across the industry. Gisairo (2016) employed descriptive cross-sectional survey while studying the effectiveness of use of biometric technology to curb fraud in medical insurance firms in Kenya. Also, Odhiambo (2016) employed descriptive cross-sectional survey in a study to evaluate the fraud management strategies adopted by insurance companies in Kenya. In China, Gong, et al. (2020) used descriptive cross-sectional survey while researching on integrated learning fraud detection method based on combination classifier fusion in the medical insurance segment.

3.4 Population of Study.

Rahi (2017) defines population as the total collection of elements about which one wants to make inferences, further the researcher disclosed that all members or subjects that exhibits similar features and characteristics makes up a population. Additionally, Mugenda and Mugenda (2003) asserted that a research population consists of participants and study objects with similar features. All regulated insurance companies in Kenya formed the study's target audience. The insurance regulator IRA reported that as of December 31, 2021, there were 56 licensed insurance businesses that specialize in general, health, and life insurance. Thus, the target population was 56 licensed insurance businesses. All the 56 insurance companies operating in Kenya were included in the study. This is because the number of respondents is small enough to make sampling statistically impossible, and it is necessary to include all the insurance companies to obtain a comprehensive understanding of the situation.

3.5 Data Collection.

The study used a questionnaire that was administered to claims, risk and marketing officers of each company or any other manager of equivalents who could be a custodian of relevant information to this study. A marketing manager or claims, risk officers and Information technology officers were used for the study as it was believed that they may have all the

relevant information required for the study. The questionnaire comprised of sections that touches on the demographics of the insurance firms, the fraud detection technologies used by insurance firms, the level of fraud in the insurance industry, effectiveness and usefulness of the fraud detection technologies and the impact of the use of technology in operations of the insurance firms. The study also used company annual financial reports, reports from insurance regulatory authorities and other relevant sources to further collect information on the insurance firm's metrics that is profitability, size, board composition and insurance services and products offered by insurance firm and also to determine the number and frequency of fraudulent claims and the effectiveness of technology used to detect the cases.

The study used the online administration of questionnaires, online questionnaires were sent to marketing, claims and risk managers. The online administration of questionnaires must have given the respondents ample time to respond on the questionnaires. Follow-up was done through calls, emails and physical visit of the insurance head offices to remind the respondents about the questionnaire and ensure they are filled. The validity and consistency of the data was tested by pilot administration of the questionnaires.

The research used online administration of questionnaires since the 56 insurance firms are distributed all over the Nairobi county and physical administration of the questionnaires would have been costly and time-consuming. Regmi et al. (2017) contend that the administration of online questionnaires can easily gather a large amount of information from participants. In a similar vein, they also appear to be feasible and useful when gathering information on delicate subjects or with samples that are typically difficult to approach.

3.6 Data Analysis.

Data preparation, investigation, presentation, testing, and presenting of final results are all included in data analysis. The completed questionnaires were used for data preparation, which included editing, coding, entering, and cleaning the data. Questionnaires were coded according to each study variable to guarantee that the margin of error is kept to a minimum and data accuracy is increased throughout the analysis. The study's approach to data analysis was quantitative.

Yamane (1973) states that descriptive statistics involves transforming large amounts of unorganized data into tables and charts with the help of percentages and frequency distributions, which aid in comprehending the data. As a result, correlation and regression analyses fall under inferential statistics. The SPSS program is utilized for data analysis and the

results are presented using tables and pie charts for clear interpretation of the research outcomes. The mean and standard deviation was used to assess and summarize the collected data. This research used logit linear regression model where dummy variable was used to determine the connection between the usage of technology and the detection of fraudulent insurance claims. Lee (2022) defines dummy variable as a numerical variable used in regression analysis to represent subgroups of the sample in the study. With dummy variable, the categorical dependent variable (Y), is transformed into a binary variable having to only two possible outcomes.

By using ordinal logit regression, the study can determine the effect of the independent variables (preferably categorical) on the dependent variable that has only two possible outcomes (Schober, 2018; Timoneda, 2021). In the context of evaluating the insurance company characteristics that influence the adoption and implementation of fraud detection technologies used in detecting fraudulent insurance claims, ordinal logit regression would be appropriate. The predictor variables were type of insurance products, company size, profitability, corporate governance characteristics and technology as the moderating variable. The dependent variable was implementation of fraud detection technologies with two only options, implemented and not implemented.

To construct the ordinal logit equation, the study created dummy variables for each category of the dependent variable (Gomila, 2021) These dummy variables would be binary, and each observation would be assigned a value of 1 for the category that it belongs to, and 0 for all other categories. For example, if an insurance company chose to use IoT technology, the dummy variable for IoT would be assigned a value of 1, while the dummy variables for ML, AI, and blockchain would be assigned a value of 0.

After creating the dummy variables, they were included as the dependent variable in an ordinal logit regression equation, along with the predictor variables of the study (type of insurance products, company size, profitability, corporate governance characteristics). The ordinal logit equation was in the form of:

$$\text{Implementation of Insurance Fraud Detection Technologies} = ln\left[\frac{p}{1-p}\right] = \beta_0 + \beta_1 Type\ of\ Insurance\ products_1 + \beta_2 Profitability_2 + \beta_3 \text{Company Size}_3 + \beta_4 \text{Corporate Governance}_4 + \varepsilon \ldots$$

The β_0 is the y-intercept, β_1, β_2, β_3 and $\beta 4$ are the coefficients for the independent variables

(type of insurance by products, profitability, size of this insurance company and corporate governance characteristics of the company) while ε is error term

The coefficients (β_1, β_2, β_3 and $\beta 4$) were estimated using a maximum likelihood estimation or other statistical methods, and were used to evaluate the relationship between the independent variables and the dependent variable. For example, a positive coefficient for the independent variable of company size might indicate that larger companies are more likely to adopt a specific technology, while a negative coefficient for the company's profitability might indicate the companies that are less profitable are less likely to adopt a specific technology. The study adopted 95% confidence interval. That means, 5 % level of significance was adopted to determine how the type of insurance products, company size, profitability, corporate governance characteristics influence the adoption and implementation of fraud detection technologies used in detecting fraudulent insurance claims.

3.7 Research Quality.

The validity and reliability of the collected data can be used to gauge the accuracy of the study. Validity refers to how well the researcher's initial intentions for assessment and measurement are reflected in the results (Mugenda & Mugenda, 2003). Reliability, on the other hand, measures the consistency of the study's findings over time (Kothari, 2017). A study is considered reliable if a repeat of the study by the same researcher would produce the same results at a different time. Therefore, the study employed a descriptive research design and employ data gathering methods such as surveys, to attain accurate and reliable results that can be generalized for future use.

3.8 Ethical Issues in Research.

These are the steps the researcher takes to protect the confidentiality of the data and participants during data collection process, the researcher took into consideration the following during data collection. The researcher was not subjected to any harm, there was dignity to participants and full consent was obtained from the participants before collecting data. The privacy of participants was protected and guaranteed, with no deception in the research questions and objectives by the researcher. The research avoided any form of biases from the primary data presentation and findings.

Further to ensure the ethical measures and standards are adhered to during the data collection process the researcher sought permission and clearance from Strathmore University Ethical

Committee (SUEC) and National Commission for Science and Technology Information (NACOSTI).

3.9 Chapter Summary.

The chapter offers descriptive design as a useful research technique for the investigation. The intended audience included the Kenya's 56 authorized insurance companies. Questionnaires sent to claim, market, or any other officer with pertinent information was used to gather the data and provide the answers to the study's questions. With the help of mean and standard deviation, the data examined and presented, and additional testing was carried out using logistic linear regression analysis.

CHAPTER FOUR

PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

The chapter presents the findings, interpretation and discussions of the study findings. First the study begins with the presentation of response rate and follows to present the demographic information of the study participants. The interpretation and discussion of the findings is guided by the study objectives.

4.2 Response Rate

The collected questionnaires were edited for accuracy, uniformity, consistency and completeness. The result on response rate is presented in Table 4.1.

Table 4.1: Response Rate

Respondents category	Administered	Valid % response
Completed	51	91.1
Incomplete	5	8.9
Total	56	100.0

Source: Research Data (2023)

A total of 56 questionnaires were distributed to the respondents whereas 51 questionnaires were properly filled and returned. This represented 91.1 percent valid response rate. Mundy (2002) stated that a response rate of 60% is adequate while a response rate greater than 70% is very good. The data collection procedures used could have attributed to this high response rate. These included pre-notification of respondents and voluntary participation by respondents, allowing respondents for ample time to fill, assurance of confidentiality and anonymity of the information and follow up calls to clarify queries from the respondents.

4.3 Demographic Information of the Insurance Companies and Respondents

Demographic information of the insurance firms and respondents were investigated. The demographic information investigated included the gender of the respondents, job position, number of years the participants have been working in the insurance sector, number of insurance branch networks and the county in which the insurance company is domiciled. The demographic information is of key interest because they can influence the adoption and implementation of fraud detection technologies. The majority of the insurance companies under study were domiciled in Nairobi City County, Kenya. Table 4.2 shows the cross tabulation of demographic information.

Table 4.2: Cross tabulation of demographic information

Demographic Factor	Category	Freq.	Percentage (%)
Gender of respondent	Male	30	59
	Female	21	41
	Total	**51**	**100**
Job position of the respondents	Claim officers	28	54.9
	Marketing officers	9	17.6
	Others (specify)	14	27.5
	Total	**51**	**100**
Number of years working in the insurance sector	Less than 5 years	7	13.7
	5 – 10 years	30	58.8
	More than 10 years	14	27.5
	Total	**51**	**100**
Number of Insurance Company Branches	0-5 branches	4	7.8
	6-10 branches	20	39.2
	Over 10 branches	27	52.9
	Total	**51**	**100**

Source: Research Data (2023)

Majority of the participants who participated in the study were males (59%). Forty-one percent (41%) of the participants were female. The results imply that majority of the employees in the claims, risk management and senior management positions among the insurance companies in Kenya are males. In the insurance industry, representation of women at board director and executive levels is improving, but progress is slow. In a report by Swiss Re Institute (2021), women represented about 23% of re/insurance company executives, 10% of chief executive officers and 8% of board chairs globally. Similarly, Birindelli and Iannuzzi (2022) indicated that women are still underrepresented in managerial and especially executive roles in the insurance industry.

The study explored the job position of the respondents in the insurance industry. The position held may impact the adoption and implementation of fraud detection technologies. Majority of the respondents who participated in the study were claim officers (54.9 percent). Furthermore, marketers formed 17.6 of the respondents while others participants holding other positions were 27.5 percent. The other respondents included risk managers and internal auditors, regional sales manager and underwriters. Claims officers and risk or marketing officers are custodian of relevant information to this study. A study by Mushunje (2019) revealed that claim and risk officers play significant roles in the measurement and proposing fraud mitigation strategies in the insurance companies. Thus, they participate in the proposition and deployment of fraud detection technologies in the insurance sector.

Majority 58.8 percent of the respondents have been working for 5-10 years. Moreover, 27.5 percent have worked for more than 10 years. Only 13.7 percent have worked for less than 5 years. The results imply that majority of the respondents have been working in the insurance sector for 5-10 years. The number of years working in a particular filed may inform level of experience, expertise and comprehension of the challenges in the insurance sector and thus inform the adoption of technological applications to reduce fraud claims and enhance the operations of the company.

The study investigated the number of insurance company branches operated by the insurance companies that formed the target population. The study found that majority (52.9 percent) of the insurance companies operated more than 10 branches. A significant number of insurance companies (38.2 percent) operated 5-10 branches countrywide. Only 7.8 percent of the insurance companies operated less than five branches. The results imply that majority of insurance companies have more than ten branch networks country-wide.

4.4 Specific characteristics of insurance companies that influence the adoption and implementation of fraud detection technologies

The study investigated the specific characteristics of insurance companies. The specific characteristics included the profitability using combined ratio and return on capital employed, size of the insurance company in terms of total assets controlled and gross premium and board characteristics. The board characteristics studied include board size, board diversity, board independence and board duality. The study assessed the featured to determine if they significantly influence the adoption and implementation of fraud detection technologies.

4.4.1 Descriptive Findings

The sections present the descriptive findings of specific characteristics of insurance companies. The descriptive findings entailed the frequencies and percentages.

4.4.1.1 Profitability

The profitability of the insurance companies was measured using two parameters. The parameters include the combined ratio and return on capital employed.

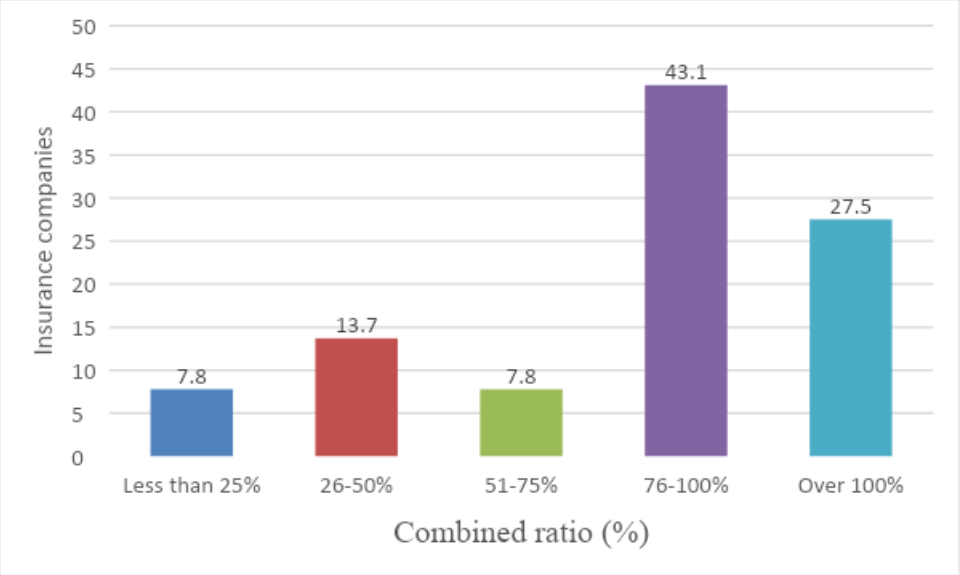

Figure 4.1: Average Combined Ratio of the Insurance Company 2018-2022

The study found that most of the insurance companies (43.1 percent) combined ratio was 76-100 percent. Further, 27.5 percent of the insurance companies had combined ratio of more than 100% while 13.7 percent had combined ratio of 26-50 percent. Further, 7.8 percent of the insurance companies had combined ratio of 51-75 percent. Only 7.8 percent had combined ratio of less than 25 percent. The combined ratio is the sum of insurance company incurred losses and expenses and to the total earned premiums. A healthy combined ratio in insurance sectors is generally considered to be in the range of 75% to 90%. Profitable insurance company is likely to adopt claim fraud mitigation strategies. Table 4.3 presents the average returns on capital employed for the insurance companies.

Table 4.3: Average ROA of this insurance company from 2018-2022

ROA Category	Number of insurance companies	Percent
Less than 2.5%	41	80.4
2.6-5%	7	13.7
5.1-7.5%	3	5.9
Total	51	100

Source: Research Data (2023)

The study established that majority of the insurance companies had been recording a return on capital employed of less than 2.5 percent. It was also noted that 13.7 percent of the insurance companies average return on capital employed was between 2.6-5 percent. Only 5.9 percent of the insurance companies recorded average return on capital employed of 5.1-7.5 percent. A ROA of over 5% is generally considered good and over 20% excellent. Insurance companies

may acquire claim fraud detection technologies if they earn extra income in form of profits.

4.4.1.2 Insurance Company Size

The size of the insurance companies was investigated. The company size was measured in terms of total assets in KES and gross earned premium. Figure 4.2 presents the categorization of the insurance company sizes by total assets.

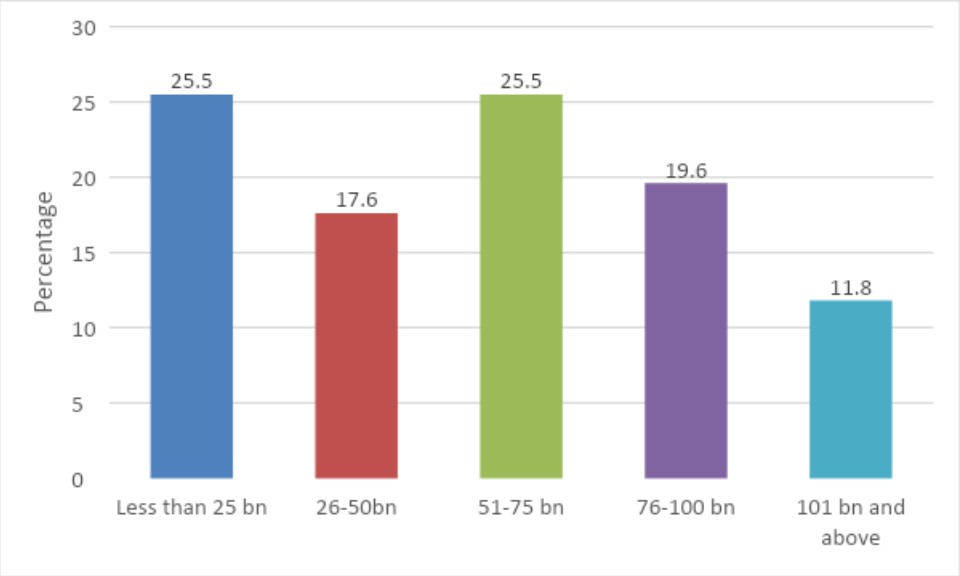

Figure 4.2: Sizes of the Insurance Companies in Terms of Total Assets (KES)

It was found that 25.5 percent of the insurance companies had total assets less than KES 25 billion. Similarly, 25.5 percent of the insurance companies had total assets worth 51-75 billion. Furthermore, 19.6 percent of the insurance companies had total assets between KES 76-100 billion while 17.6 percent had total assets of KES 26-50 billion. Only 11.8 percent of the insurance companies had total asset more than KES 101 billion. The size of the company may inform the desire to implement fraud detection technologies to enhance company operations.

Insurers can use data from IoT devices such as the various components of smart homes, automobile sensors, and wearable technologies to better determine rates, mitigate risk, and even prevent losses arising from the claims in the first place. Table 4.4 shows the gross earned premium in KES for the insurance companies in Kenya.

Table 4.4: Gross earned premium in KES

Gross earned premium in (categorized)	Frequency	Percent
Less than 5 billion	10	19.6
5-10 billion	12	23.5
11-16 billion	7	13.7
17-20 billion	21	41.2
21 billion and above	10	19.6
Total	51	100

Source: Research Data (2023)

Most of the insurance gross earned premium was between KES 17-20 billion. Twelve (23.5 percent) of the insurance companies gross earned premium was between KES 5 to 10 billion. Furthermore, 19.6 percent of the insurance company had gross earned premiums of more than KES 21 billion. Likewise, 19.6 percent of the insurance company had a gross earned premium of less than KES 5 billion while 13.7 percent had a gross earned premium of KES 11-16 billion.

4.4.1.3 Board characteristics

The board characteristics investigated in the study include board size, board gender diversity, board independence, and board duality. Figure 4.3 presents the board sizes of the insurance companies.

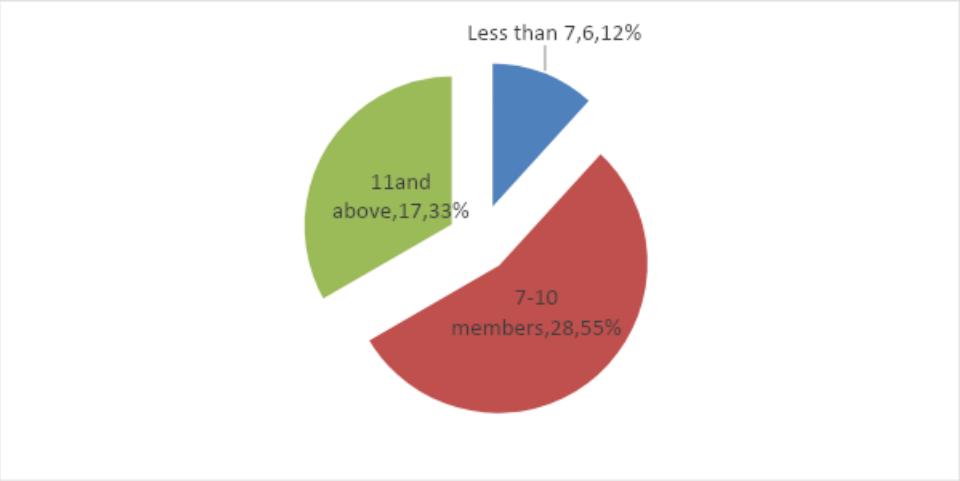

Figure 4.3: Size of the board members

Majority (55 percent) of the insurance companies had a board size of 7-10 members. Thirty-three percent (33 percent) of the insurance company had a board size of more than 10 board members while 12 percent had a board size of less than 7 members. The size of the board determines the efficiency of the board in doing the oversight of the company. In the context of the study, the board may be involved in the discussion of strategies to mitigate fraud risks

associated with claims and the proposition of fraud mitigation technologies to detect fraud claims. Table 4.5 presents the gender diversity of the board in terms of the number of females on the insurance company board.

Table 4.5: Gender diversity of the Board

Number of females in the Board	Frequency	Percent
Less than 20%	27	52.9
21-30%	8	15.7
31-40%	9	17.6
41-50%	5	9.8
50% and above	2	3.9
Total	51	100

Source: Research Data (2023)

It was found that majority (52.9 percent) of the insurance company comprised less than 20 percent of the female board members. 17.6 percent of the insurance companies' boards were made up of 31-40 percent female board members while 15.7 percent of the insurance companies' boards comprised 21-30 percent of the female board members. Furthermore, 9.8 percent of the insurance companies' boards were made up of 41-50 percent female members. Only 3.9 percent of the insurance companies had female board members more than 50 percent of the total board size. The diversity of the board in terms of gender representation may enhance the diversity of ideas required in the oversight of the company. The diversity of ideas may be helpful in the adoption and implementation of fraud detection technologies. Figure 4.4 presents the board duality structure of the insurance companies.

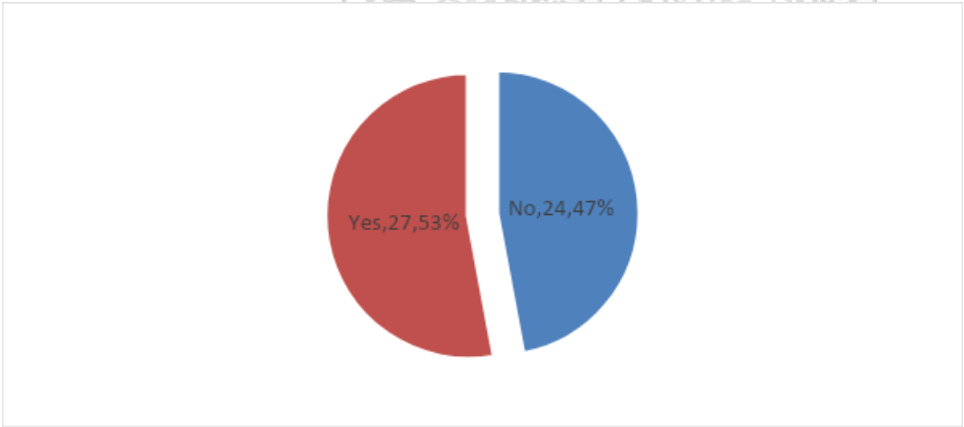

Figure 4.4: Board duality

The study findings showed that a slight majority (53 percent) of the insurance companies had a CEO of the company also as the chairman of the board of directors. Forty-seven percent of the insurance companies had separate CEO and chairman of the board. Board duality may act

as a deterrent in the decision of whether a company adopts a fraud detection mechanism. A company CEO that is both the chairman and company CEO may present a monopoly of ideas that may hinder the adoption of fraud detection technologies. Table 4.6 presents the percentage number of independent members on the board.

Table 4.6: Percentage number of independent members in the Board

Percentage Category	Frequency	Percent
Less than 20%	6	11.8
21-30%	9	17.6
31-40%	18	35.3
41-50%	13	25.5
50% and above	5	9.8
Total	51	100

Source: Research Data (2023)

The study established that 35.3 percent of the insurance companies' boards was made of 31-40 percent independent board members. 25.5 percent of the insurance companies had 41-50 percent independent board members while 17.6 percent had 21-30 percent of independent board members. Only 9.8 percent of the insurance companies was made up of more than 50 percent independent board members whereas 11.8 percent had 20 percent and below independent board members. The presence of the independent board members is helpful in promoting independent views that may facilitate the adoption and implementation of fraud detection technologies among the insurance companies. Independent directors add value to a company by increasing accountability and providing objective judgment of board functions and decisions. A board with a higher proportion of outside directors has better management oversight.

4.4.2 Logistic Regression Model

A logistic regression model was fitted to examine how specific characteristics of insurance companies influence the adoption and implementation of fraud detection technologies. Logistic regression was adopted because the study sought to determine whether insurance companies had implemented the fraud detection technologies and what salient firm characteristics influences the adoption of these fraud detection technologies. Table 4.7 presents the logistic regression model results.

Table 4.7: Logistic regression of specific characteristics of insurance companies, adoption and implementation of fraud detection technologies

Variable	marginal effects (dy/dx)	B	S.E.	Wald	Sig.	Exp(B)
Type of Insurance by-products						
All insurance				9.499	0.05	
General insurance	0.614905	2.085**	1.219	5.599	0.018	8.045
Life Insurance	0.486484	2.145**	1.053	4.153	0.042	8.542
Motor insurance	0.5265	2.383**	0.965	6.096	0.014	10.842
Health Insurance	0.23593	1.084**	0.427	6.449	0.011	2.955
Profitability						
Return on capital employed				0.758	0.944	
Combined ratio	0.33034	1.407***	0.394	12.762	0.000	4.083
Size of this Insurance company						
Total assets (KES bn)				4.451	0.348	
Gross earned premium (KES bn)	0.32186	1.46**	0.717	4.145	0.042	4.307
Corporate Governance Characteristics of the Company						
Board duality				5.435	0.246	
Board size	0.33272	1.827**	0.867	4.44	0.035	6.2152
Board gender diversity	0.114125	0.482	0.469	1.055	0.304	0.618
Board independence	0.37693	1.591***	0.594	7.177	0.007	4.907
Constant		0.974	1.678	0.337	0.562	0.378

*<p0.10, **p< 0.05, *** p < 0.01, Exp (B)/Odds ratio (OR)
Source: Research data (2023)

The type of insurance by products is positively and statistically significant in influencing adoption and implementation of fraud detection technologies. The marginal effects for general insurance is 0.614905 implying that insurance companies dealing with general insurance products are likely to adopt and implement fraud detection technologies by 0.614905 units (61.5%). It was also found that the marginal effects for insurances companies dealing with life insurance was 0.486484 percentage points implying that insurance companies dealing with life insurance will likely adopt and implement fraud detection technologies by 48.6 percent. For

motor insurance, the marginal effect is 0.5265 indicating that insurance companies dealing with motor insurance will likely adopt and implement fraud detection technologies by 52.7 percent. Finally, the marginal effect for health insurance is 0.23593 indicating that insurance companies dealing with health insurance will likely adopt and implement fraud detection technologies by 23.6 percent. The type of insurance products that an insurance company deals with is likely to influence the adoption and implementation of fraud detection technologies. For instance, general and motor insurance products are likely to record high cases of fraud claims compared to health and life insurance. Thus, type of insurance products that are prone to fraud claims will likely prompt the insurance companies to seek claim fraud detection technologies. According to IRA (2022), insurance products in the Kenyan market include and not limited to, auto insurance, general insurance, medical insurance, life insurance, fire insurance, aviation insurance. Segodi and Sibindi (2022) noted that type of insurance products experience different levels of fraud claims and the type of mitigation strategy.

It was also established that there was a positive and significant association between profitability, the adoption and implementation of fraud detection technologies by insurance companies. With return on capital employed being a base reference, combined ratio had a positive and statistically significant association with the adoption and implementation of fraud detection technologies by insurance companies. The marginal effects for combined ratio was 0.33034 implying that profitability is likely to influence the adoption and implementation of fraud detection technologies by 33.0 percent. A profitable insurance company will likely set aside earnings to acquire, install and maintain the fraud detection technologies. The fraud detection technologies are cost intensive in terms of the acquisition of the fraud detection technologies, operations, and maintenance. The growth of the insurance industry in the country is hindered, according to reports from industry players, because of the prevalence of unchecked fraud. Fraudulent insurance claims increase the net incurred claims ratio of insurance companies. The findings are in tandem with Copeland (2022) who indicated that fraud and high management costs reduce insurance companies' bottom lines. In another study, Amaresh (2022) indicated that with the help of A.I., the insurance industry may enhance profitability by as much as 40% by 2030, all while lowering operational costs by the same percentage. Similarly, Walker (2022) noted that business spending on artificial intelligence has enabled financial fraud detection, and prevention strategy platforms are expected to rise from a little over $6.5 billion in 2022 to more than $10 billion in 2027.

The size of the insurance company was found to have a positive and significant association with the adoption and implementation of fraud detection technologies. With total assets being a base reference, the gross earned premium had a positive and statistically significant association with the adoption and implementation of fraud detection technologies by insurance companies. The marginal effect for company size was 0.32186 implying that insurance company size is likely to influence the adoption and implementation of fraud detection technologies by 32.1 percent. Like the adoption of any new technology, the size of an insurance company significantly impacts which fraud detection methods it chooses to implement. Large insurance companies in terms of assets are more likely to resolve the development or acquisition of fraud detection technologies.

Market-leading companies are more inclined to embrace new technologies because they are better positioned to reap the benefits of doing so. Furthermore, bigger and more profitable enterprises are more likely to have the monetary resources necessary for procuring and installing a new technology even amid inefficient capital markets. In terms of risk distribution, large insurance companies are able to distribute risks, associated with new initiatives since they have more options when it comes to which technologies to implement and can test out new ones without having to shut down their existing ones. Moreover, with the economies of scale associated with large companies, insurance companies are likely to spread the various fixed costs involved with adoption across a larger number of units. Small enterprises with few resources are more prone to choose a short-term or passive viewpoint towards innovations and technological adoptions, making them more susceptible to external context changes. The results concur with Kijkasiwat and Phuensane (2020) who stated that access to capital is a key factor in the adoption of technologies in an organisation. The findings are further supported by Nguyen et al. (2022) who suggest that larger firms usually have sufficient resources to try out new technologies and have more capabilities to bear the risks and expenses of implementing the innovations.

Corporate governance characteristics of the insurance company is positively and statistically significant in influencing adoption and implementation of fraud detection technologies. With board duality as the base reference, board gender diversity is not statistically significant predictor in the adoption and implementation of fraud detection technologies by the insurance companies. The marginal effects for board size is 0.33272 implying that board size is likely to influence the adoption and implementation of fraud detection technologies by 33.3 percent. Board size is the number of board members of an organization board of management. Board

size affects the quality of decisions, more information sharing build vast links with external surrounding, procure more scarce assets, on the other hand, it leads to communications and coordination problems, higher free-loader obstacles and knowledge sharing cost, less expression of notion and thoughts. Further, the marginal effects for board independence was 0.37693 percentage points implying that board independence is likely to influence the adoption and implementation of fraud detection technologies by 37.7 percent. Board independent members act for the benefit of shareholders as they can mitigate any negative and bias advisory of the company. Independent directors add value to a company by increasing accountability and providing objective judgment. A board with a higher proportion of outside directors has better management oversight. Independent board can effectively monitor and oversight the operations of the firm and in doing so enhance the openness of ideas including the desire to implement certain technological processes in the company. A board with a higher proportion of outside directors has better management oversight. Board independence are pillars of corporate governance and firm technological growth.

The prevention and detection of fraud within insurance firms is primarily the responsibility of the management under the oversight of those charged with governance. Auditors, along with other members of the corporate governance and reporting ecosystem, also have an important role. Although the adoption of fraud detection technologies is tipped to reduce the cases of fraudulent insurance claims, there are many factors involved in the adoption of such technologies. Indeed, technology is not a panacea and the human element also comes into play. There is an opportunity for all involved – including management and boards, auditors, and regulators – to focus more on corporate culture and behaviours to support fraud detection. In a study by Rohmatin, et al. (2021), corporate governance plays a critical oversight of the organization and is thus important in fraud detection and prevention mechanisms. Similarly, Maravelaki, et al. (2021) indicated that the board of management paves the way for the implementation of technological processes in an organization.

4.5 Fraudulent Claims in The Insurance Sector

The study sought to determine the number of insurance companies that had implemented technology in handling insurance claims. The results are presented in Figure 4.5.

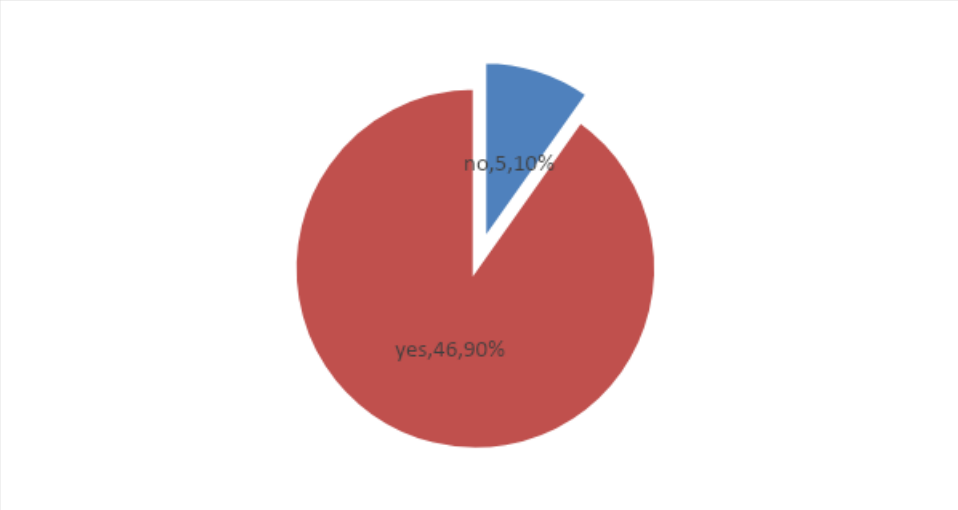

Figure 4.5: The company has implemented technology in handling insurance claims

Among the studied insurance companies, the majority 90 percent (of 46 insurance companies) had implemented the technology in handling insurance claims. Only 10% (10 insurance companies) had not implemented it. The results imply that the use of technologies to detect fraud claims has been increasing among insurance. With rising fraud claims, insurance companies have been implementing detection technologies to detect fraud claims. The key to stopping fraudulent actions before real harm is done is to be vigilant and have anti-fraud technology to detect suspicious activities early on. Examples of fraud detection technologies include deployed by insurance companies include Blockchain in insurance, Artificial Intelligence, the Internet of Things, Machine Learning, and Robotic Process Automation. In a study by Oundo (2019) on the use of machine learning algorithms in the healthcare industry, Oundo (2019) claimed that by utilizing techniques like Logistic Regression and SVM, organizations are able to identify claims as being correct or needing further investigation by auditors. Further, the study investigated if the insurance companies had encountered fraudulent insurance claims during their day-to-day operations. The results are presented in Figure 4.6.

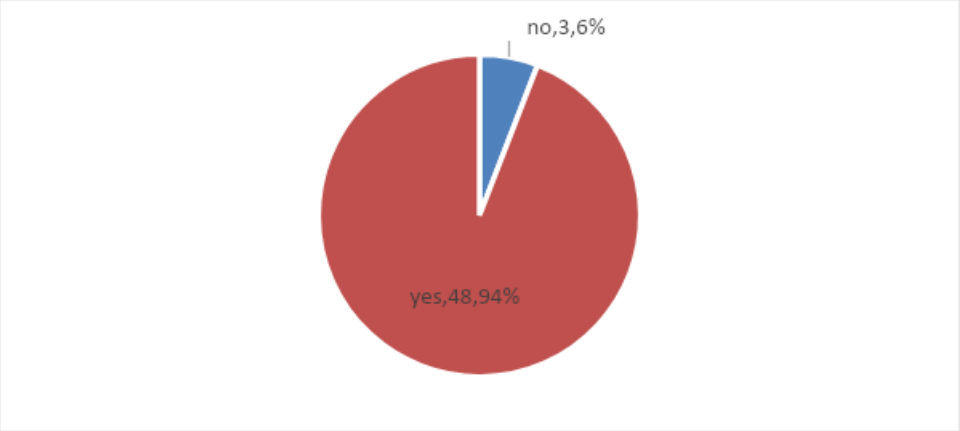

Figure 4.6: Encountered fraudulent insurance claim

Majority 94 percent of the insurance companies had encountered fraudulent insurance claims. Only 6 percent (3 insurance companies) had not encountered fraudulent claims. The results signify that there are high cases of fraudulent claims and thus the need to deploy fraud detection technologies to mitigate the menace. Insurance fraud is diverse and prevalent in all insurance fields. A significant proportion of insurance claims are fraudulent leading to high premiums to honest customers and contributing to damaging insurers' image and reputation. Insurance fraud is any action done with the purpose to gain a fraudulent output from an insurance process. Mostly insurance fraud includes complicated financial transactions which are mainly conducted by white-collar criminals, and also sometimes by a person having specialized knowledge and criminal intent. Insurance Fraud is the scariest threat to most insurance companies. These companies are facing increasing fraudulent cases of insurance in the past few years. These fraudulent cases increase the cost of premiums which causes enormous problems for both policy holders and also to insurance companies. The results are in tandem with Patil (2019) that rising insurance fraud cases not only increase the cost of insurance companies but also lead to increased premiums. Thus, insurance companies must have a proper risk management framework to minimize the number of frauds. Furthermore, the study sought to determine if the number of fraudulent insurance claims has been increasing among insurance companies. The results are shown in Figure 4.7.

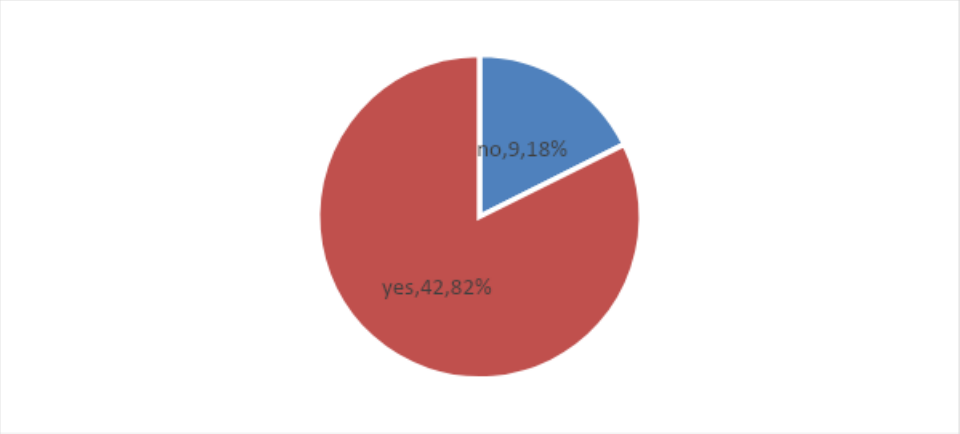

Figure 4.7: The number of fraudulent insurance claims has been increasing in your firm

Majority 82 percent (42 insurance companies) acknowledged that the number of fraudulent insurance claims has been increasing among the insurance companies. The results imply that cases of fraudulent claims have been on the rise. This phenomenon necessitates the need for technologies to detect fraud claims among insurance companies. Increasing insurance fraud has various implications for insurance companies including, increased cost of doing business, direct impact on premium rates, and huge claim reserve ratios. In a report by the German Insurance Association (2019), it is estimated that one in ten claims reported can be put down to insurance fraud, generating overall losses of EUR 4 billion.

The study sought to investigate the chances that when the insured raises a claim, it will be fraudulent. The responses were ranked on a scale of 1 to 10 where 1 represents extremely low and 10 represents extremely high. For the purpose of interpretation, the responses from a scale of 1-5 were summed together as extremely low while responses from 6-10 as summed together as extremely high. The results are presented in Table 4.8.

Table 4.8: Chances that when insured raise a claim it will be fraudulent

	extremely low		**1**		**2**		**3**		**4**		**5**		**6**		**7**		**extremely high**		**Mean**
	f	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	
Chances that when insured raise a claim it will be fraudulent	0	0.0%	6	11.8%	8	15.7%	16	31.4%	3	5.9%	9	17.6%	3	5.9%	3	5.9%	3	5.9%	4

f is frequency, % is percentages
Source: Research Data (2023)

It was indicated that chances that a raised claim will be fraudulent were low (64.8 percent). Nonetheless, 35.2 percent indicated that the chances that a raised claim was fraudulent were

high (35.2 percent). This is an indication that cases of fraudulent claims are on the rise and the need to detect them using an appropriate detection technology is important. A study by Mwashi (2017) indicated that fraud claims continue to characterize the insurance industry costing insurance firms a lot of money. Insurance fraud can be committed by applicants, policyholders, claimants, service providers, agents, brokers, and company employees. AKI report (2021) argues that an estimated 25% of insurance industry income is fraudulently claimed. The study further sought to investigate whether the assertion that detecting and preventing fraudulent insurance claims is difficult. The responses were put on a scale of 1 to 10, with 1 representing "strongly agree" and 10 representing "strongly disagree". For the purpose of interpretation, the responses on a scale of 1-5 were summed together as strongly agree while responses from 6-10 as summed together as strongly disagree. The results are shown in Table 4.9.

Table 4.9: Level of agreement that detecting and preventing fraudulent insurance claims is difficult

	Strongly disagree		**1**		**3**		**4**		**5**		**6**		**7**		**8**		**9**		**Strongly agree**		**Mean**
	f	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	
Level of agreement that detecting and preventing fraudulent insurance claims is difficult	0	0.0	3	5.9%	3	5.9	3	5.9	21	41.2	9	17.6%	3	5.9	6	11.8	3	5.9	0	0.0	5

f is frequency, % is percentages

Source: Research Data (2023)

A simple majority 58.9 percent (30 insurance companies) agreed that detecting and preventing fraudulent insurance claims is difficult. However, 41.1 percent (21 insurance companies) disagreed that detecting and preventing fraudulent insurance claims is difficult. It can be hard to confirm if a claim is fraudulent, and in case of suspicion, more details such as receipts, payment transaction history, and similar documents are requested. This phenomenon necessitates the need for technologies to detect fraud claims among insurance companies. Effective fraud detective technologies should be able to prevent, detect, report, and remedy fraud in the insurance policy. The challenge is that insurance fraud is hard to identify and it is estimated that the number of detected fraud cases represents only a small percentage of the actual cases. Insurance fraud is a big concern and various insurance stakeholders including insurers, regulators and insurance associations are making a concerted effort to

prevent insurance claim fraud.

The study sought to determine whether the insurance company had implemented technology for insurance fraud detection. The results are shown in Table 4.10.

Table 4.10: Company implemented technology for insurance fraud detection

Company implemented technology for insurance fraud detection	Frequency	Percent
No	6	11.8
Yes	45	88.2
	51	100.0

Source: Research Data (2023)

The study found that the majority 88.2 percent (of 45 insurance companies) have implemented technology for insurance fraud detection. Only 11.8 percent of insurance companies have not implemented technology for insurance fraud detection. The results imply that many insurance companies have adopted certain technologies to aid in the detection of claim fraud. In the case of insurance fraud, machine learning models help in identifying what a normal claim looks like to establish a baseline. Once that baseline is defined, they can identify abnormalities and notify insurers. During claim processes, anomaly detection helps in examining legitimate customer claims. Artificial intelligence and predictive analytics are shaping the future of the entire industry, giving significant competitive advantages to insurance companies in detecting fraud claims. Predictive analytics is the use of historical data, machine learning algorithms, and statistical modeling to foresee future events. Predictive analytics in insurance fraud detection is the use of data and statistical techniques to automatically identify fraud patterns and reveal potentially fraudulent claims. Insurers can also deploy AI to assess risks, detect fraud, and reduce human errors with the help of AI in the insurance industry. AI in insurance offers better and streamlined customer services along with easier and quicker claims processing.

4.6 Fraud Detection Technologies in the Insurance Industry

The study investigated the fraud detection technologies being employed by insurance companies to detect insurance claims. The results are shown in Figure 4.8.

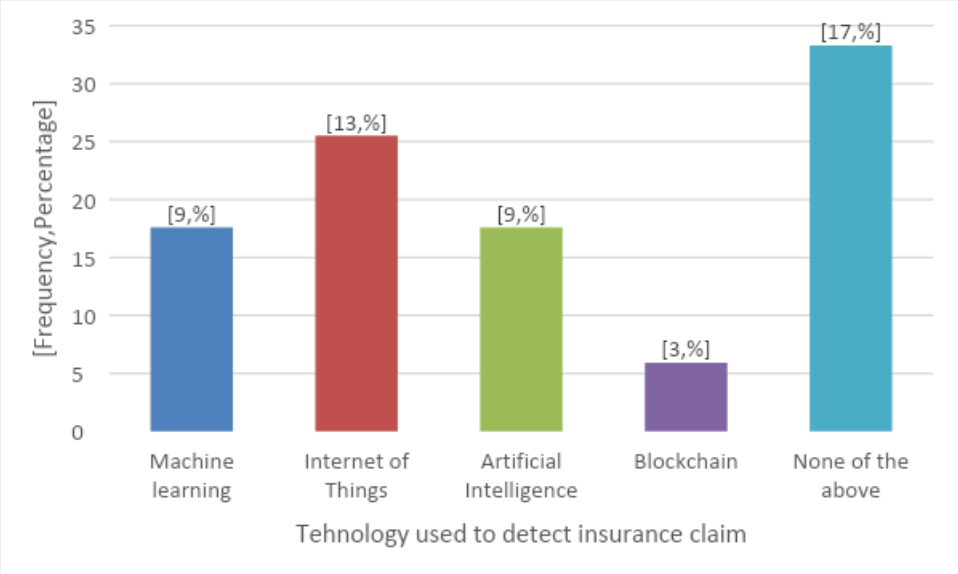

Figure 4.8: Fraud Detection Technologies Used by Insurance Companies in Kenya

It was established that the common fraud detection technologies include the Internet of Things (25.5 percent), machine learning (17.6 percent), artificial intelligence (17.6 percent), and blockchain (5.9 percent). Nonetheless, the insurance companies were using other forms of fraud detection (33.3 percent). IoT is a network of physical items connected to and exchange data with other systems and devices through the internet. The findings are in congruence with Fu et al. (2019) who explored the use of IoT technology in the insurance industry and found that IoT devices such as sensors, wearables, and telematics could be used to collect data on the insured item, such as a car, property, or a person. Similarly, Singh and Tripathi (2021) found that IoT devices such as smart home devices and connected cars could be used to collect data on the insured property and help detect any fraud claim.

Machine learning has also been widely used in fraud detection within the insurance industry. ML algorithms can analyze large amounts of data to identify potentially fraudulent activities by identifying patterns and anomalies in data. The findings concur with Choudhary et al. (2019) who highlighted that ML algorithms could improve the accuracy of fraud detection by identifying complex patterns and anomalies that may be difficult to identify manually. Similarly, a study by Zhong et al. (2021) utilized an ML-based approach to detect fraudulent auto insurance claims and reported the reliability of ML in detecting claim fraud.

With Artificial intelligence, AI algorithms analyze large amounts of data to identify patterns that indicate potentially fraudulent activities. According to Li et al. (2018), AI algorithms can be used to detect fraudulent claims by analyzing the claimant's behavior patterns, such as claim frequency, location, and history. Sharma and Bokoro (2020) proposed a blockchain and AI-based secure and intelligent system to detect health insurance fraud in their study on Blockchain and AI-empowered Healthcare Insurance Fraud Detection.

A blockchain data format makes it possible to create a digital log of transactions and share it among a distributed network of computers. The decentralized nature of blockchain technology has the potential to reduce fraudulent activities by providing a secure and transparent platform. According to Zheng et al. (2018), blockchain technology can help in preventing fraud by allowing insurers to access a shared database of claims data, which reduces the possibility of duplicate or false claims. The findings are in tandem with Lo and Wang (2019) who highlighted that blockchain technology could improve the efficiency of fraud detection by reducing the time required to verify claims and providing a more transparent process.

Training is essential in the use of technologies in detecting insurance claim fraud. The study sought to investigate if there exists any training or education on the use of the technology used to detect and prevent fraudulent insurance claims. The results are shown in Figure 4.9.

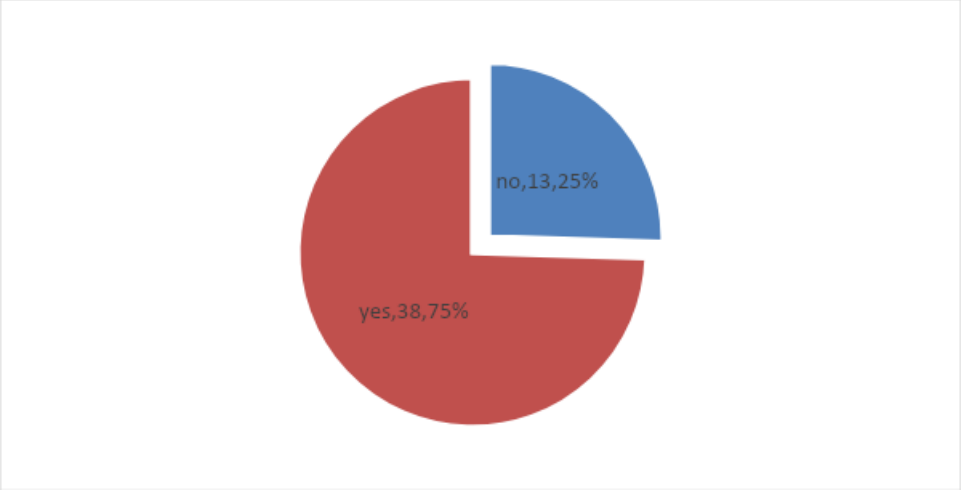

Figure 4.9: Received any training or education on the use of the technology used to detect and prevent fraudulent insurance claims

Majority (75 percent) of the users were undertaken training on the use of the technology used to detect and prevent fraudulent insurance claims. Only 25 percent did not go through certain forms of training on the use of fraud detection technologies in the insurance sector. Training on the use of fraud detection technologies is critical. Training helps understand how fraud

detection technologies are deployed and also in creating awareness among insurance staff on how to identify and prevent claim fraud. The insurers may need to empower their staff through training and have a business model that integrates the technology needed to effectively fight fraud. According to Patil (2019), insurance companies need to invest more in providing training and education to fraud investigators so that fraud cases can be restricted.

The study sought to determine the extent insurance companies are relying on fraud detection technologies to detect insurance. The responses were ranked on a scale of 1 to 10 with 1 being low extent and 10 being high extent. For the purpose of interpretation, scales 1-5 were summed together as low extent while responses from 6-10 were summed together as high extent. The results are presented in Table 4.11.

Table 4.11: Level of reliance on the insurance fraud detection technologies

	Frequency	**Percent**
Low extent	3	5.9
High extent	48	94.2
Total	51	100

Source: Research Data (2023)

Majority (94.2 percent) of the insurance companies were relying to a high extent on the fraud detection technologies to detect insurance fraud. Only 5.9 percent (3 insurance companies) relied on fraud detection technologies to detect insurance fraud to a low extent. The results imply that the use of fraud detection technologies to detect insurance fraud in the insurance sector has significantly risen. Technological tools such as artificial intelligence, the Internet of Things, and blockchain can be used by insurers to detect and prevent insurance fraud. The use of AI in claims fraud detection is quite helpful, increasing client happiness and minimizing losses related to fraudulent claims. With the number of fraudulent claims rising in the insurance industry, machine learning, and AI algorithms can quickly identify patterns, enabling them to spot outliers and dubious requests in real time. The findings are in line with Fraud, (2014) who indicated that the use of technology to detect fraud in claims, underwriting, and other areas continues to climb and more insurers are embracing the use of tech systems as a key component of their anti-fraud strategies.

The study sought to investigate factors that should be considered in choosing fraud detection technologies. The critical factors include cost and effectiveness, usefulness, efficiency, speed, user friendly, ease to integrate with current systems and learn the methods of fraud detection, compatibility with customized data parameters, and data availability and processing. The other

factors include the technological infrastructure required & skilled personnel able to operate and interpret, type of policies, regions, insureds, and circumstances leading to losses.

The study investigated the problems the insurance companies are facing in implementing insurance fraud detection technologies. The problems include low acceptance and resistance to change, cost and expenses associated with these technologies, system manipulation by the providers, lack of adequate information and technical know-how, inadequate capital, lack of sharing of information in the industry, resistance to change, and legal and data privacy issues.

The respondents were asked to indicate whether in the future more insurance companies will rely on technologies for detecting fraud claims. According to the majority of the respondents, fraud detection technologies will remain essential because it is the only way to counter fake and fraudulent claims. Moreover, technology is inevitable due to the current workspace where most business will be done online, enhancing the efficiency of operations among the insurance companies and helping in analyzing human behavior, future business trends, and analyses of newer fraud models. Numerous insurance companies are resorting to technology to remain competitive and minimize claim fraud. Compared to the cost of adopting and sustaining the technologies, technologies are worth investing in as it significantly reduces losses arising from fake claims. The respondents noted that the technologies for detecting claim fraud will be sustainable in the future though this will require continuous improvement of these technologies. Technologies and fraud are very dynamic and thus technologies for detecting fraud ought to continuously adjust to adapt to the changes in the business environment.

The respondents were asked to indicate whether fraud detection technologies have changed the way the insurance firm does business. The findings of the study are presented in Table 4.12.

Table 4.12: The fraud detection technologies have changed the way the insurance firm does business

Response	Frequency	Percent
No	3	5.9
Yes	48	94.1
Total	51	100.0

Source: Research Data (2023)

Majority 94.1 percent agreed that fraud detection technologies have changed the way the insurance firm does business. This implies that the technologies used in detecting fraud claims

have been useful among insurance companies. Detection of fraud has helped insurance companies minimize cases of fraud claims that cost the insurance companies huge fraudulent costs.

Furthermore, the respondents were requested to indicate if the use of technologies has reduced the instances of paying out fraudulent claims. The findings of the study are presented in Table 4.13.

Table 4.13: Use of technologies has reduced the instances of paying out fraudulent claims

	Frequency	Percent
No	4	7.8
Yes	47	92.2
Total	51	100.0

Source: Research Data (2023)

Majority 92.2 percent indicated that technologies has reduced the instances of paying out fraudulent claims. This signifies that technologies have been effective in deterring fraud claims in the insurance industry. Insurance providers and consumers are impacted by insurance fraud, which is a serious problem because insurers frequently try to offset fraud losses by raising premiums. According to Coalition Against Insurance fraud (2021), the key to stopping fraudulent actions before real harm is done is to be vigilant and have anti-fraud technology to detect suspicious activities early on; as a result, anti-fraud leaders must make the difficult decision to increase budgets in order to continue investing in well-known and dependable tools like automatic monitoring and procure newer anti-fraud solutions and techniques like Blockchain and identity verification technology. Mansour (2020), indicated that most insurance companies have resorted to machine learning, predictive analytics, and data mining techniques to strengthen fraud detection

The study further sought to determine the ease of use of the technology in detecting and preventing fraudulent insurance claims. The responses were put on scale of 1 to 10, with 1 representing "not easy" and 10 representing "easy". For the purpose of interpretation, the responses from scale 1-5 were summed together as not easy while responses from 6-10 as summed together as easy. The results are shown in Table 4.14.

Table 4.14: Ease of use of the technology in detecting and preventing fraudulent insurance claims

	Frequency	Percent
Not easy	22	43.1
Easy	29	56.9
Total	51	100.0

Source: Research Data (2023)

A slight majority (56.9 percent) of the respondents agreed that it is easy to use the technology in detecting and preventing fraudulent insurance claims. However, 43.1 percent of the respondents indicated that using the technologies for detecting fraud claims in the insurance sector is not easy to use. This implies that proper inductive training is required for users to comprehend the use of fraud detection technologies. The inductive training should be continuous and objective to align with dynamics detection technologies.

The study further sought to determine the effectiveness of the technologies in detecting fraudulent claims. The responses were put on a scale of 1 to 10, with 1 representing "not effective" and 10 representing "very effective". For the purpose of interpretation, the responses from a scale of 1-5 were summed together as not effective while responses from 6-10 as summed together as very effective. The results are shown in Table 4.15.

Table 4.15: Effectiveness of the technologies in detecting fraudulent claims

	Not effective		4		5		8		9		Very effective		Mean
	f	%	f	%	f	%	f	%	f	%	f	%	
On a scale of 1 to 10, how effective are the technologies in detecting fraudulent claims?	0	0.0%	3	5.9%	8	15.7%	18	35.3%	19	37.3%	3	5.9%	8

f is frequencies, % is percentages
Source: Research Data (2023)

Majority of the respondents (78.5 percent) agreed that the technologies are effective in detecting fraudulent claims. This implies that the technologies have significantly helped in combating fraud claims in the insurance industry. This has enabled insurance companies to minimize losses related to fraud claims and boost their profitability margin. Fraud detection and prevention technologies have made enormous strides through data-driven innovation, including computing, data mining, analytics, machine learning, and other forms of artificial intelligence, developing different mechanisms. More advanced technologies allow for more dynamic analysis of insurance claim data.

The study further sought to determine the likelihood to recommend the use of fraud detection technologies by insurance companies. The responses were put on a scale of 1 to 10, with 1 representing "not likely" and 10 representing "not likely". For the purpose of interpretation, the responses from a scale 1-5 were summed together as not likely while responses from 6-10 as summed together as likely. The results are shown in Table 4.16.

Table 4.16: Likelihood to recommend the use of the insurance fraud detection technologies

	Not likely		**6**		**7**		**8**		**9**		**Most likely**		**Mean**
	f	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	**f**	**%**	
Likelihood to recommend the use of the insurance fraud detection technologies	0	0.0%	3	5.9%	6	11.8%	9	17.6%	15	29.4%	18	35.3%	9

f is frequencies, % is percentages
Source: Research Data (2023)

Majority (94.1 percent) of the respondents were likely to recommend the use of the insurance fraud detection technologies. This implies that the detection technologies are playing critical roles in minimizing fraud claims. The respondents were asked to indicate how useful have been the technologies, such as machine learning and data analytics in detecting fraudulent insurance claims. The results are presented in Table 4.17.

Table 4.17: Usefulness of technologies in detecting fraudulent insurance claims

	Not useful		5		7		8		9		Very useful		Mean
	f	%	f	%	f	%	f	%	f	%	f	%	
To what extent do you believe technologies, such as machine learning and data analytics, are useful in detecting fraudulent insurance claims?	0	0.0%	3	5.9%	3	5.9%	17	33.3%	16	31.4%	12	23.5%	9

f is frequencies, % is percentages
Source: Research Data (2023)

A majority (94.1 percent) of the respondents indicated that the technologies are very useful in detecting fraud claims in the insurance industry. The technology identifies the root causes of fraudulent activities and uses the data to foresee fraud and combat it proactively. By maximizing the use of technology and data analytics, insurers reduce the number of manual interventions in the claim management process. This reduces turnaround times and frees up insurance agents, allowing them to focus on more valuable, high-impact tasks. Leveraging technology-based solutions can assist in identifying fraud red flags and also reduce disruption to the claims process, ensuring that client turnaround times are top of mind and that legitimate claims are not unnecessarily delayed.

AI fraud detection technologies not only automate the fraud detection process but also identifies fraud patterns, allowing early flagging and prompt response to any potential incidents. As the number of clients increases, claims adjusters are put under more pressure and should either sacrifice accuracy or speed in the claims process. Predictive analytics another technology that insurers use to fight insurance fraud provide insights into people's actions by tracking and interpreting their browsing history, clicks, location and help insurers determine whether or not policyholders' claims are trustworthy. By detecting the fraud claim, the insurance minimizes losses associated with fraud claims and puts necessary measures to prevent the presentation of fake claims. The insurance company thus increases the gross premium. In the case of insurance fraud, machine learning models help in identifying what a

normal claim looks like to establish a baseline. Once that baseline is defined, they can identify abnormalities and notify insurers.

The respondents were asked to indicate if they recorded an improvement in the accuracy of fraud detection since implementing technology. The results are shown in Table 4.18.

Table 4.18: Any improvement in the accuracy of fraud detection since implementing technology

	Frequency	Percent
No	3	5.9
Yes	48	94.1
Total	51	100.0

Source: Research Data (2023)

Majority of the respondents (94.1 percent) acknowledged that there has been improvement in the accuracy of fraud detection since implementing technology. The findings imply that fraud detection technologies are reliable in detecting fraud claims in the insurance industry. According to the respondents, the most effective technologies in detecting fraud claims are machine learning (49.0 percent), data analytics (23.5 percent), artificial intelligence (17.6 percent) and block chain (3.8 percent). The use of technologies if well implemented will significantly help the faster settlement of insurance claims, increase fraud detection and prevention, enhance efficiency and make it much easier to eradicate fraudulent claims hence trust on the industry which has been tainted for the longest time.

The study sought to comprehend how insurance are balancing the use of technology with other fraud detection methods, such as manual investigations and customer profiling. The findings are presented in Table 4.19.

Table 4.19: Balancing the use of technology with other fraud detection methods, such as manual investigations and customer profiling

	Frequency	Percent
I only use technology as a fraud detection method	6	11.8
I use technology more than I use other fraud detection methods	3	5.9
I use both technology and other fraud detection methods in equal measures	39	76.5
I use technology less than I use other fraud detection methods	3	5.9
Total	51	100

Source: Research Data (2023)

It was indicated that majority of the insurance companies are using technology and other fraud detection methods in equal measures. This implies that through methods of detecting fraud are on the rise, traditional methods of detecting technologies are still being deployed. The traditional methods include a review of documentation and evidence.

Despite the benefits of technologies, data privacy issues remain an impending issue. According to the respondents, data privacy and security are being enhanced in the insurance sector by signing the NDAs and limiting access to users, not authorizing data to unauthorized parties, implementing and following data protection guidelines set by the insurance management, staff training, and sensitization on data privacy and security. However, the specific challenges encountered in the use of technologies to detect fraud include evolving methods of fraud, fraud is evolving at a higher rate and there is a need to evolve the technology, technology integration issues, fewer data to analyze, and human error during the implementation of processes, very expensive and more involving and the techniques are not able to completely detect fraud, sometimes use of investigators more viable.

The respondents were asked to indicate the return on investment of technological investment for detecting fraud. The results are presented in Figure 4.10.

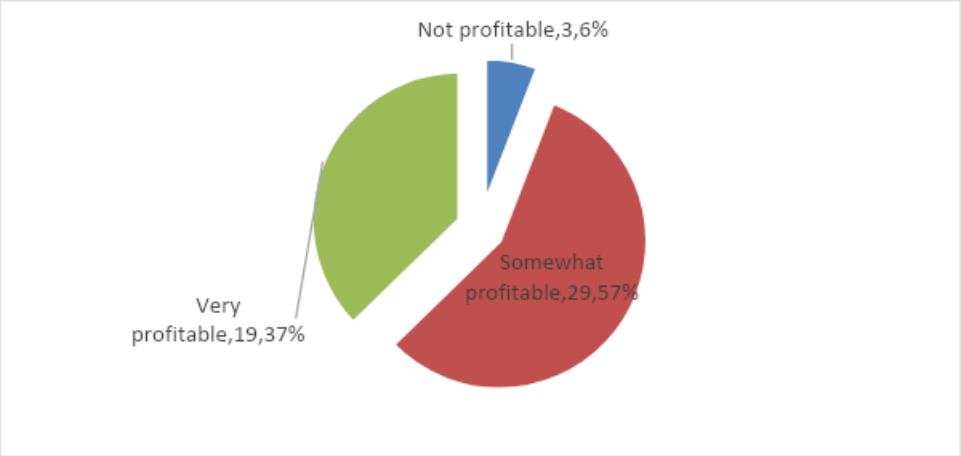

Figure 4.10: ROI of insurance fraud detection technologies

Majority of the respondents (57 percent) indicated that technological investments for detecting fraud are somewhat profitable. Thirty-seven percent (37 percent) were of the view that the use of technological investment for detecting fraud are profitable. The results imply that technological investment for detecting fraud have enhanced profitability of the insurance companies by minimizing losses arising from fraudulent acclaims.

4.7 Chapter Summary

The chapter presented the study findings and interpretation. The chapter presented the response rate where 91.1 percent response rate was attained and demographic information. Majority of the participants who participated in the study were males while forty-one percent of the participants were female. Of the respondents who participated in the study were claim officers. Majority of the respondents have been working for 5-10 years. In terms of branch network, most of the insurance companies operated more than 10 branches. The chapter proceed with presenting the study findings and interpretations as guided by the objectives. The common fraud detection technologies include used by the insurance companies was internet of things followed by machine learning, artificial intelligence and block chain where a majority of the respondents indicated that the technologies are very useful in detecting fraud claims in the insurance industry. The type of insurance by products, size of the insurance company, profitability, board size and board independence are significant company characteristics that influence the adoption and implementation of fraud detection technologies. However, board gender diversity is not statistically significant predictor in the adoption and implementation of fraud detection technologies by the insurance companies.

CHAPTER FIVE

DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The chapter discusses the study findings, conclusions and recommendations are presented in this chapter. The presentation of the summary of major findings, conclusions and recommendations has been conducted according to the study objectives. The study objectives were to establish the fraud detection technologies used by Kenyan insurance firms to detect and prevent fraudulent insurance claims, examine how specific characteristics of insurance companies influence the adoption and implementation of fraud detection technologies and evaluate the usefulness and efficacy of technologies in detecting fraudulent insurance claims. The conclusions and recommendations are derived from the study findings as guided by the objectives. The chapter further proceeds to outline the area for further research and the limitation of the study. The chapter ends with a summary of the chapter content.

5.2 Discussion

The discussion of the findings is guided by the study objectives. The presentation of the findings was followed by interpretation and comparison with studies that agree and those that do not.

5.2.1 Fraud Detection Technologies Used by Kenyan insurance firms to Detect and prevent fraudulent insurance claims

The first objective of the study was to establish the fraud detection technologies used by Kenyan insurance firms to detect and prevent fraudulent insurance claims. It was established that the common fraud detection technologies used by insurance companies were the Internet of Things followed by machine learning, artificial intelligence, and blockchain. Nonetheless, the insurance companies were using other forms of fraud detection. IoT is a network of physical items connected to and exchange data with other systems and devices through the internet. The findings are in congruence with Fu et al. (2019) who explored the use of IoT technology in the insurance industry and found that IoT devices such as sensors, wearables, and telematics could be used to collect data on the insured item, such as a car, property, or a person. Similarly, Singh and Tripathi (2021) found that IoT devices such as smart home devices and connected cars could be used to collect data on the insured property.

Machine learning has also been widely used in fraud detection within the insurance industry. ML algorithms can analyze large amounts of data to identify potentially fraudulent activities by identifying patterns and anomalies in data. The findings concur with Choudhary et al. (2019) who highlighted that ML algorithms could improve the accuracy of fraud detection by identifying complex patterns and anomalies that may be difficult to identify manually. Similarly, a study by Zhong et al. (2021) utilized an ML-based approach to detect fraudulent auto insurance claims and reported promising results.

With Artificial intelligence, AI algorithms analyze large amounts of data to identify patterns that indicate potentially fraudulent activities. According to Li et al. (2018), AI algorithms can be used to detect fraudulent claims by analyzing the claimant's behavior patterns, such as claim frequency, location, and history. Sharma and Bokoro (2020) proposed a blockchain and AI-based secure and intelligent system to detect health insurance fraud in their study on Blockchain and AI-empowered Healthcare Insurance Fraud Detection and found them to be effective in detecting claim fraud.

A blockchain data format makes it possible to create a digital log of transactions and share it among a distributed network of computers (Munich American Reassurance, 2020). The decentralized nature of blockchain technology has the potential to reduce fraudulent activities by providing a secure and transparent platform. According to Zheng et al. (2018), blockchain technology can help in preventing fraud by allowing insurers to access a shared database of claims data, which reduces the possibility of duplicate or false claims. The findings are in tandem with Lo and Wang (2019) who highlighted that blockchain technology could improve the efficiency of fraud detection by reducing the time required to verify claims and providing a more transparent process.

5.2.1 Specific Characteristics of insurance companies that Influence the Adoption and Implementation of fraud detection technologies

The second objective of the study was to examine how specific characteristics of insurance companies, such as size, type, and profitability, influence the adoption and implementation of fraud detection technologies. The type of insurance by-products is positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. The results imply that insurance companies dealing with general insurance products, dealing with life insurance, motor insurance, and health insurance products are likely to adopt and implement fraud detection technologies. The type of insurance products that an insurance

company deals with is likely to influence the adoption and implementation of fraud detection technologies. For instance, general and motor insurance products are likely to record high cases of fraud claims compared to health and life insurance. Thus, the type of insurance products that are prone to fraud claims will likely prompt the insurance companies to seek claim fraud detection technologies. According to IRA (2022), insurance products in the Kenyan market include, and not limited to, Auto insurance, General Insurance, Medical insurance, life insurance, fire insurance, and aviation insurance. Segodi and Sibindi (2022) noted that types of insurance products experience different levels of fraud claims

It was also established that there was a positive and significant association between profitability and the adoption and implementation of fraud detection technologies by insurance companies. With return on capital employed being a base reference, the combined ratio had a positive and statistically significant association with the adoption and implementation of fraud detection technologies by insurance companies. The results imply that profitability is likely to influence the adoption and implementation of fraud detection technologies. A profitable insurance company will likely set aside earnings to acquire, install and maintain fraud detection technologies. The fraud detection technologies are cost-intensive in terms of the acquisition of the fraud detection technologies, operations, and maintenance. The growth of the insurance industry in the country is hindered, according to reports from industry players, because of the prevalence of unchecked fraud. Fraudulent insurance claims increase the net incurred claims ratio of insurance companies. The findings are in tandem with Copeland (2022) who claims that fraud and high management costs reduce insurance companies' bottom lines. In another study, Amaresh (2022) indicated that with the help of A.I., the insurance industry may enhance profitability by as much as 40% by 2030, all while lowering operational costs by the same percentage. Similarly, Walker (2022) noted that business spending on artificial intelligence-enabled financial fraud detection, and prevention strategy platforms are expected to rise from a little over $6.5 billion in 2022 to more than $10 billion in 2027.

The size of the insurance company was found to have a positive and significant association with the adoption and implementation of fraud detection technologies. With total assets being a base reference, the gross earned premium had a positive and statistically significant association with the adoption and implementation of fraud detection technologies by insurance companies. The results of the study imply that insurance company size is likely to influence the adoption and implementation of fraud detection technologies. Like the adoption of any new technology, the size of an insurance company significantly impacts which fraud detection

methods it chooses to implement. Large insurance companies in terms of assets are more likely to resolve the development or acquisition of fraud detection technologies. The results concur with Kijkasiwat and Phuensane (2020) who stated that access to capital is a key factor in the creative process. The findings are further supported by Nguyen et al. (2022), who suggest that larger firms usually have sufficient resources to try out new technologies and have more capabilities to bear the risks and expenses of implementing innovations.

Corporate governance characteristics of the insurance company are positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. With board duality as the base reference, board gender diversity is not a statistically significant predictor in the adoption and implementation of fraud detection technologies by insurance companies. The study indicated that board size is likely to influence the adoption and implementation of fraud detection technologies. Board size is the number of board members of an organization's board of management. Board size affects the quality of decisions, more information sharing build vast links with external surrounding, and procure more scarce assets, on the other hand, it leads to communications and coordination problems, higher free-loader obstacles and knowledge sharing cost, and less expression of notion and thoughts.

Further, board independence is positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. This implies that board independence is likely to influence the adoption and implementation of fraud detection technologies. Board independent members act for the benefit of shareholders as they can mitigate any negative effect. Independent directors add value to a company by increasing accountability and providing objective judgment. A board with a higher proportion of outside directors has better management oversight. Independent boards can effectively monitor and oversight the operations of the firm and in doing so enhance the openness of ideas including the desire to implement certain technological processes in the company. A board with a higher proportion of outside directors has better management oversight. Board independence are pillars of corporate governance and firm technological growth. In a study by Rohmatin, et al. (2021), corporate governance plays a critical oversight of the organization and is thus important in fraud detection and prevention mechanisms. Similarly, Maravelaki, et al. (2021) indicated that the board of management paves the way for the implementation of technological processes in an organization.

5.2.3 Usefulness and efficacy of technologies in detecting fraudulent insurance claims

The third objective of the study was to evaluate the usefulness and efficacy of technologies in detecting fraudulent insurance claims. The majority of insurance companies indicated that the technologies are very useful in detecting fraud claims in the insurance industry. The technology identifies the root causes of fraudulent activities and uses the data to foresee fraud and combat it proactively. By maximizing the use of technology and data analytics, insurers reduce the number of manual interventions in the claim management process. This reduces turnaround times and frees up insurance agents, allowing them to focus on more valuable, high-impact tasks. Leveraging technology-based solutions can assist in identifying fraud red flags and also reduce disruption to the claims process, ensuring that client turnaround times are top of mind and that legitimate claims are not unnecessarily delayed.

Furthermore, the majority of insurance companies indicated that technologies have reduced the instances of paying out fraudulent claims. This signifies that technologies have been effective in deterring fraud claims in the insurance industry. Insurance providers and consumers are impacted by insurance fraud, which is a serious problem because insurers frequently try to offset fraud losses by raising premiums. According to Coalition Against Insurance Fraud (2021, the key to stopping fraudulent actions before real harm is done is to be vigilant and have anti-fraud technology to detect suspicious activities early on; as a result, anti-fraud leaders must make the difficult decision to increase budgets in order to continue investing in well-known and dependable tools like automatic monitoring and procure newer anti-fraud solutions and techniques like Blockchain and identity verification technology. Mansour (2020), indicated that most insurance companies have resorted to machine learning, predictive analytics, and data mining techniques to strengthen fraud detection.

5.3 Conclusion

The study concludes that the Internet of Things was the most popular technology used by Kenyan insurance firms to detect and prevent fraudulent insurance claims, followed, by machine learning, artificial intelligence, and blockchain. The type of technology used to detect fraudulent insurance claims depends on the nature, type, and quantity of insurance fraud claims.

A conclusion is further made that the type of insurance by-products is positively and statistically significant in influencing the adoption and implementation of fraud detection technologies. The insurance companies dealing with general insurance products are likely to adopt and implement fraud detection technologies followed by motor insurance, life insurance,

and finally health insurance in that order. The size of the insurance company, profitability, board size, and board independence are significant company characteristics that influence the adoption and implementation of fraud detection technologies. Board gender diversity is not a statistically significant predictor in the adoption and implementation of fraud detection technologies by insurance companies.

Finally, the study concludes that technologies are useful and efficient in detecting fraudulent insurance claims. The technology identifies the root causes of fraudulent activities and uses the data to foresee fraud and combat it proactively. By maximizing the use of technology and data analytics, insurers reduce the number of manual interventions in the claim management process. Leveraging technology-based solutions can assist in identifying fraud red flags and also reduce disruption to the claims process, ensuring that client turnaround times are top of mind and that legitimate claims are not unnecessarily delayed.

5.4 Limitations of the Study

The study faced conceptual limitations as it only focused on the fraud detection technologies used by Kenyan insurance firms to detect and prevent fraudulent insurance claims. Technology is a dynamic process that changes rapidly and is faced with other factors like customer needs, data privacy issues, and regulatory policies. The study relied much on primary data. This may have brought about methodological limitations relating to the technique of analysis.

5.5 Recommendations

There are several technologies used to detect and prevent fraudulent insurance claims. The technologies include blockchain, artificial intelligence, the Internet of Things, machine learning, and robotic process automation. The study recommends the deployment of more than one technology. This is informed by the different nature of fraud claims and dynamics associated with fraudsters and detection technologies. The insurance company ought also to evaluate the strengths and weaknesses associated with each of the technologies before settling on one to deploy in the company.

Various specific characteristics of insurance companies influence the adoption and implementation of fraud detection technologies. Before implementing any insurance fraud detection technology, the insurance company may need to consider the kind of insurance products it is dealing with. Some insurance products are more prone to fraud claims than others. Moreover, profitability and company size define the ability of the insurance company to implement fraud-detecting technologies. A profitable insurance company will likely set aside

earnings to acquire, install and maintain the fraud detection technologies. The fraud detection technologies are cost-intensive in terms of the acquisition of the fraud detection technologies, operations, and maintenance. Large insurance companies in terms of assets are more likely to resolve the development or acquisition of fraud detection technologies. The board features also inform the oversight, expert opinion, and risk management. Thus, an effective board is essential in the implementation of fraud detection technologies by insurance companies.

With increasing insurance fraud claims, insurance companies ought to implement fraud detection technologies that suit the needs of the organization. The needs are parametrized by the usefulness and efficacy of the technologies in detecting fraudulent insurance claims. Leveraging technology-based solutions can assist in identifying fraud red flags and also reduce disruption to the claims process, ensuring that client turnaround times are top of mind and that legitimate claims are not unnecessarily delayed.

5.6 Suggestions for further research

The study faced conceptual limitations as it only focused on the fraud detection technologies used by Kenyan insurance firms to detect and prevent fraudulent insurance claims, specific characteristics of insurance companies that influence the adoption and implementation of fraud detection technologies, and usefulness and efficacy of technologies in detecting fraudulent insurance claims. Technology is a dynamic process that changes rapidly and is faced with other factors like the customer needs, data privacy issues, and regulatory policies. Future studies may include these concepts in the implementation of technologies to detect and prevent fraudulent insurance claims. The study relied much on primary data. This may have brought about methodological limitations relating to the technique of analysis. Future studies may collect secondary data on firm characteristics and how they influence the usage of technologies to detect and prevent fraudulent insurance claims measured using the number of fraudulent claims recorded.

5.7 Summary of the chapter

The chapter outlined the introduction and discussion of findings. Conclusions and recommendations were presented according to the study objectives. Further, suggestions for further research and limitation of the study were conducted. The chapter ended with a summary of the chapter.

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Appendix I: Research Questionnaire

ASSESSMENT OF THE FRAUD DETECTION TECHNOLOGIES USED BY KENYAN INSURANCE FIRMS IN DETECTING AND PREVENTING FRAUDULENT INSURANCE CLAIMS

Section A: Personal Information

1. Gender of the respondent. Male [ ] Female [ ]

2. 1. Please indicate your job position by ticking in the appropriate box.

Check all that apply.

- ☐ Claims officer
- ☐ Marketing officer
- ☐ Other (please specify): _____

3. 2. How long have you worked in the insurance sector?

Check all that apply.

- ☐ Less than 5 years
- ☐ 5 - 10 years
- ☐ More than 10 year

B. Company Profile.

Provide brief information about your insurance company

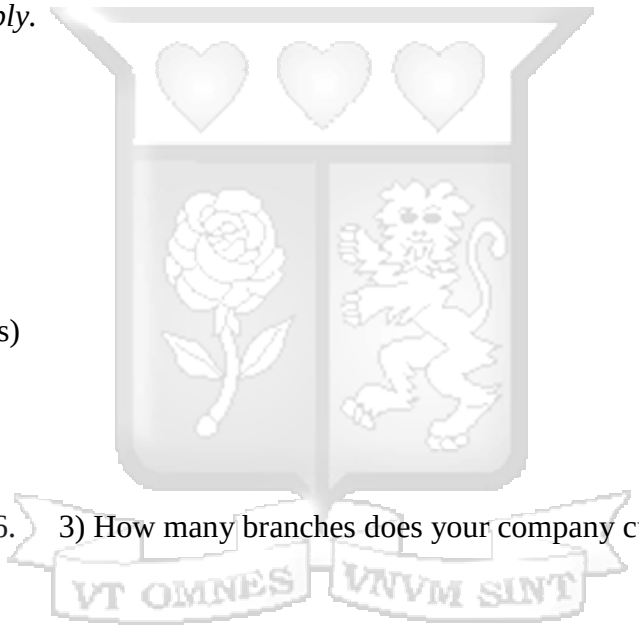
4. 1) In which County is the company domiciled?

_____

5. 2) For how long has your company been operating?

Check all that apply.

- ☐ (1-5 years)
- ☐ (5-15 years)
- ☐ (15-50 years)
- ☐ (over 50 years)



6. 3) How many branches does your company currently operate?

Check all that apply.

- ☐ (0-5 brunches)
- ☐ (5-10 brunches)
- ☐ (over 10 brunches)

_____

Profitability

7. What was the average combined ratio of this insurance company from 2018-2022?

Less than 25% [ ] 26-50% [ ] 51-75% [ ] 76-100% [ ]
Over 100% [ ]

8. Indicate the average ROA of this insurance company from 2018-

2022?

Less than 5% [ ] 6-10% [ ] 11-16% [ ] 17-20% [ ]
21-25% [ ] 26% and above [ ]

Size of this Insurance company

9. Indicate the size of this insurance company in terms of total assets (KES)

Less than 25 bn [ ] 26-50bn [ ] 516-75 bn [ ] 76-100 bn [ ]
101 bn and above [ ]

10. Gross earned premium in (KES)

Less than 5 bn [ ] 5-10bn [ ] 11-16 bn [ ] 17-20 bn [ ]
21bn and above [ ]

Corporate Governance Characteristics of the Company

11. Size of the board members

Less than 7 [ ] 7-10 members [ ] 11and above [ ]

12. Percentage of number of female directors to board size (Board gender diversity)

Less than 20% [ ] 21-30% [ ] 31-40% [ ] 41-50% [ ]
50% and above [ ]

13. Board duality

Yes [ ] No [ ]

14. Percentage number of independent members in the Board

Less than 20% [ ] 21-30% [ ] 31-40% [ ] 41-50% [ ]
50% and above [ ]

15. 5) What insurance products does your company offer?

16. 7) Has your company employed fraud detection technologies in evaluating insurance claims?

Check all that apply.

- [ ] Yes
- [ ] No

SECTION B: FRAUDULENT CLAIMS IN THE INSURANCE SECTOR

17. 1) Have you ever encountered a fraudulent insurance claim?

Check all that apply.

- [ ] Yes
- [ ] No

18. 2) Has there been an increase in the number of fraudulent insurance claims in your firm in the recent past?

Check all that apply.

- [ ] Yes
- [ ] No

19. 3) On a scale of 1 to 10, with 1 indicating a very low likelihood and 10 indicating a very high likelihood, what is the probability of an insurance claim being fraudulent when filed?

Mark only one oval.

Low

1

2

3

4

5

6

7

8

9

10

High

20. On a scale of 1 to 10, with 1 representing "strongly agree" and 10 representing "strongly disagree," to what extent do you agree with the statement that detecting and preventing fraudulent insurance claims is difficult?

Mark only one oval.

Strongly disagree

1

2

3

4

5

6

7

8

9

10

Strongly agree

SECTION C: TECHNOLOGIES IN FRAUD DETECTION.

21. 1) What fraud detection technology is your company currently using to detect insurance claim?

Mark only one oval.

- Machine learning
- Internet of Things
- Artificial Intelligence
- Blockchain.
- None of the above.

22. Have you received any training or education on the use of the technology used to detect and prevent fraudulent insurance claims?

Check all that apply.

- Yes
- NO

23. On a scale of 1 to 10, how easy is it to use the technology in detecting and preventing fraudulent insurance claims?

Mark only one oval.

Not effective

1 ◯

2 ◯

3 ◯

4 ◯

5 ◯

6 ◯

7 ◯

8

9

10

Very effective

24. On a scale of 1 to 10, how effective are the technologies in detecting fraudulent claims?

Mark only one oval.

Not effective

1

2

3

4

5

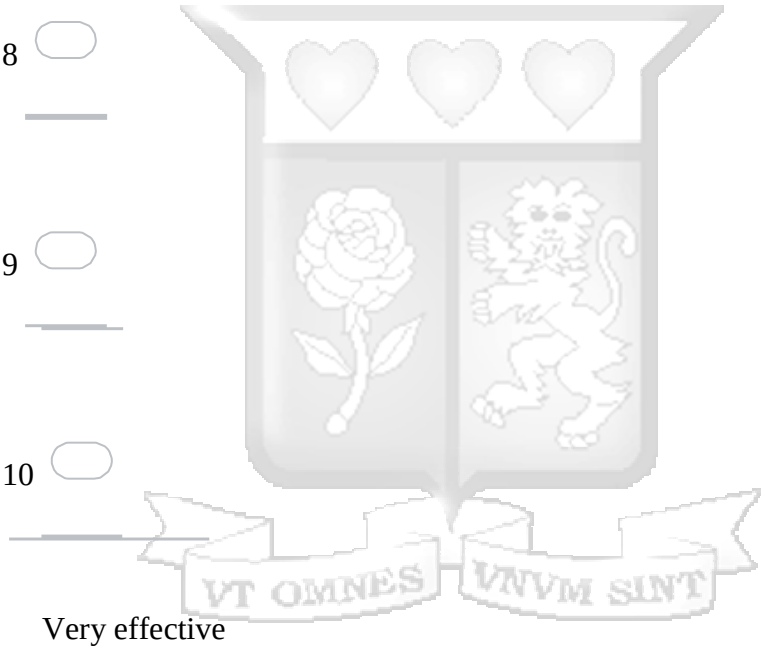
6

7

8

9

10



Very effective

25. On a scale of 1 to 10, how likely are you to recommend the use of the fraud detection technologies for insurance Fraud detection?

Mark only one oval.

Not likely

1

2

3

4

5

6

7

8

9

10

Most likely

26. 6) To what extent do you believe technologies, such as machine learning and data analytics, are useful in detecting fraudulent insurance claims?

Mark only one oval.

Not useful

1

2

3

4

5

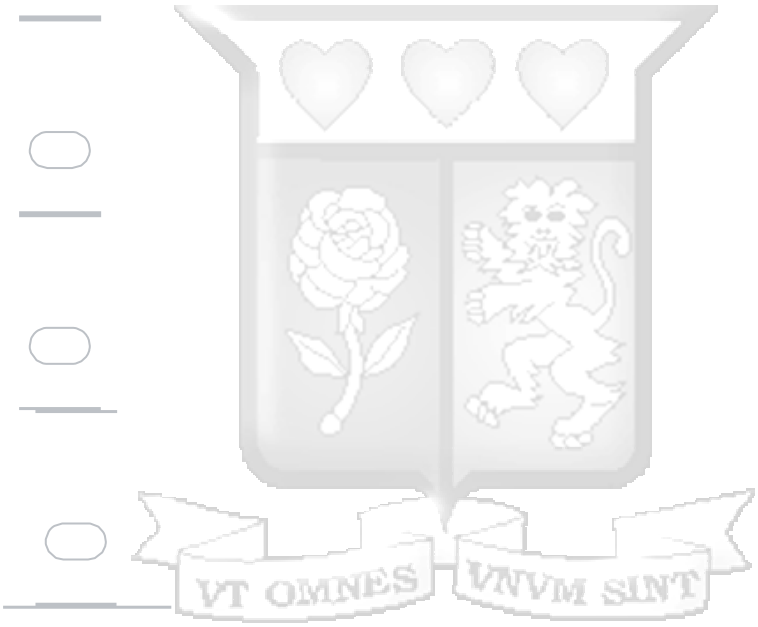
6

7

8

9

10



Very useful

27. 7) Have you seen an improvement in the accuracy of fraud detection since your company started using insurance fraud detection technologies?

Check all that apply.

- [ ] Yes
- [ ] NO

28. 8) In your opinion, what are the most effective technological tools for detecting fraudulent insurance claims?

29. 9) How do you see technology impacting the future of fraud detection in the insurance industry?

30. 10) How do you balance the use of technology with other fraud detection methods, such as manual investigations and customer profiling?

Check all that apply.

- ☐ I only use technology as a fraud detection method
- ☐ I use technology more than I use other fraud detection methods
- ☐ I use both technology and other fraud detection methods in equal measures
- ☐ I use technology less than I use other fraud detection methods

31. 11) How do you ensure the data privacy and security when using technology for fraud detection?

32. 12) Are there any specific challenges or limitations you have encountered when using technology for fraud detection?

33. 13) What is your opinion on the ROI of fraud detection technologies among the insurance companies?

Check all that apply.

- ☐ Not profitable
- ☐ Somewhat profitable
- ☐ Very profitable

Appendix II: Research Budget

Printing	5,000
Photocopying	10,000
Traveling	13,000
Research Asst.	40,000
Publication Fee	20,000
Miscellaneous	10,000
Total	**102,000**

Appendix III: Institutional Ethical Review Approval.

Strathmore UNIVERSITY

31st March 2023

Mr Owuor Moses Agot,
Owuor.Moses@strathmore.edu

Dear Mr Owuor,

RE: To Establish the Modern Technologies used by Kenyan Insurance Firms to Detect and Prevent Fraudulent Insurance Claims

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1652/23.** The approval period is from 31st **March 2023 to 30th March 2024.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 48 hours of notification
iv. Any changes, anticipated or otherwise, that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 48 hours
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

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

Yours sincerely,

for: **Dr Ben Ngoye,**
Secretary; SU-ISERC

Cc: Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
31-Mar-2023
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA

Appendix IV: NACOSTI Research License.

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **957775**

Date of Issue: **11/April/2023**

RESEARCH LICENSE

This is to Certify that Mr.. Moses Agot Owuor of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: Assessment the modern technologies used by Kenyan Insurance firms to prevent and detect fraudulent insurance claims for the period ending : 11/April/2024.

License No: **NACOSTI/P/23/25069**

957775

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

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

See overleaf for conditions