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Nature of Consumer-Type Insurance Fraud and the Size of Associated Financial Losses among Medical Insurance Providers in Kenya

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ABSTRACT

Medical insurance fraud is currently a pressing challenge in Kenya, yet its detection and scale, especially within consumer-initiated schemes, remain under-examined in scholarly literature. This study sought to investigate the relationship between the nature of detected consumer-type medical insurance fraud and the size of the associated financial losses among insurance providers in Kenya. Anchored in the Fraud Hexagon Theory and the Red Flag System Approach, the study employed a descriptive cross-sectional design using a non-reactive methodology. A census of 53 fraud cases detected over a six-month period across 14 medical insurance providers was conducted. Data were gathered from organizational records, and analysis was performed using SPSS version 28. Descriptive statistics assessed forms of fraud, while chi-square tests and Pearson correlation was used to examine associations between fraud characteristics and financial impact. Findings showed that falsification of claims, pharmacy-related fraud, and member substitution were the most prevalent forms of insurance fraud. The study established that while the nature of fraud (e.g., form, perpetrator, motivation) contributes to variability in loss magnitude, there is limited use of predictive detection models within the sampled organizations. The study concludes that fraud detection strategies, including the application of red flag indicators and institutional capacity to act on early signals, are critical to minimizing financial losses. It recommends the institutionalization of predictive analytics, integration of fraud typologies into detection protocols, and establishment of a national guideline on fraud detection and reporting. The study also contributes to existing criminological and financial fraud literature by providing reliable empirical data on the typologies and economic impact of medical insurance fraud in the Kenyan context. Limitations and areas for future inquiry are discussed.

Keywords: Medical insurance fraud, fraud detection, consumer fraud, fraud magnitude, non-reactive design

INTRODUCTION

Empirical studies on fraud within insurance systems increasingly underscore the complexity of fraudulent behavior and the institutional challenges of detection and control (Association of Certified Fraud Examiners [ACFE], 2020; Ghee & Button, 2015; Salleh et al., 2018; Vousinas, 2019). While the broader fraud literature frequently engages with conceptual categories such as corruption, asset misappropriation, and financial statement manipulation, medical insurance fraud has emerged as a distinctive phenomenon due to its multifaceted structure, specialized billing systems, and diverse actors including providers, consumers, and insurers (Li et al., 2008; du Preez et al., 2025). This distinctiveness has made medical insurance fraud a focal point in global fraud risk management discourses, with provider fraud receiving the lion's share of scholarly attention (Angima & Omondi, 2016; Legotlo & Mutezo, 2018; Villegas-Ortega, et al., 2021). However, this provider-centric orientation has inadvertently obscured the role of consumers as significant perpetrators of fraud, despite evidence suggesting their growing involvement in fraudulent claims, identity misrepresentation, and misuse of insurance products (ACFE, 2020; Nabrawi & Alanazi, 2023).

As medical insurance systems evolve, consumer-related fraud has become an increasingly salient challenge. Defined broadly, consumer medical insurance fraud involves intentional deception by insured individuals to obtain unwarranted benefits or coverage, often through means such as falsifying claims, doctor shopping, document forgery, or misrepresenting eligibility (Thornton et al., 2013; Angima & Omondi, 2016). Yet, despite its prevalence and cost implications, consumer-perpetrated fraud remains underexplored in both academic and regulatory discourse, especially in non-Western contexts like Kenya (Association of Kenya Insurers (AKI), 2020). This gap is problematic given that fraudulent practices by consumers not only increase premiums and reduce trust in insurance systems but also hinder the effective delivery of health services (Button & Cross, 2017; Ghee & Button, 2015). Moreover, the lack of reliable statistics, definitional clarity, and methodological consistency has limited the ability of insurers and policymakers to gauge the magnitude of the problem or respond with evidence-based interventions (Dyck et al., 2024).

The Kenyan context exemplifies these challenges. Medical insurance fraud is widely acknowledged within the local industry, with aggregate losses reaching substantial levels annually (Insurance Regulatory Authority [IRA], 2021). However, the framing of fraud as a monolithic category—wherein consumer, provider, and insurer fraud are treated as indistinguishable—has inhibited understandings of the specific forms, motivations, and impacts of consumer-driven schemes. While a few studies have documented the prevalence of provider fraud (Angima & Omondi, 2016), scholarly inquiry into consumer-type medical insurance fraud remains virtually absent. This lacuna persists despite growing evidence from other jurisdictions suggesting that consumer fraud can rival, and in some cases exceed, the cost and frequency of provider fraud (Salleh et al., 2018; ACFE, 2020).

Compounding this analytical gap is a set of methodological limitations in existing research. Much of the literature relies on ethnographic case studies, survey-based perceptions, or administrative records that do not distinguish between actors or forms of fraud (Li et al., 2008; du Preez et al., 2025; Ghee & Button, 2015). These approaches rarely engage with theoretical models capable of linking fraud occurrence to measurable organizational, behavioral, and temporal variables. In contrast, recent theoretical advancements—such as the Fraud Hexagon model (Vousinas, 2019) and the Red Flag Systems Approach (Stamler et al., 2014)—offer robust conceptual tools for analyzing the antecedents and consequences of fraudulent activity. These theoretical models are especially pertinent in the Kenyan setting, where medical insurance systems operate within a constrained regulatory environment characterized by low data transparency, fragmented reporting practices, and varied detection capacities across providers (IRA, 2021; AKI, 2021). Despite the attempts to regulate fraudology towards uniform standards, the endeavors are ill-developed and usually limited to reactive challenges (Angima & Omondi, 2016). Moreover, there is no established framework for determining the relationship between specific forms of consumer fraud and their associated financial costs, time to detection, or underlying motivational structures. As such, both scholarly and policy discourses lack the empirical foundation needed to develop predictive models or targeted interventions.

This study sought to fill these conceptual, empirical, and methodological gaps by examining the correlation existing between the type of medical insurance fraud detected and the magnitude of the fraud to the insurance providers in Kenya. The research was guided by the Fraud Hexagon and the Red Flag Systems Approach that put together a complete picture of fraud as an individual behavioral activity, an organizational behavioral process, and a fraud abuse detection mechanism. Through this, the study provides a theoretically and empirically sound analysis of an overlooked but essential attribute of insurance fraud.

LITERATURE REVIEW

This section explains some of the previous works done on nature and extent of detected health care insurance fraud. It also specifies the theoretical framework as well as the conceptual framework which we have based our study on.

A. Magnitude and Global Burden of Medical Insurance Fraud

Medical insurance fraud is regarded as one of the costliest white-collar crimes in both developed and developing countries. Its impact extends far beyond monetary loss, causing serious long-term challenges to healthcare systems, distorting insurance markets, and eroding public trust. Globally, healthcare fraud is estimated to cost trillions of dollars, a figure that continues to rise with the expansion of healthcare services and the digitalization of claims systems (Ghee & Button, 2015; ACFE, 2020). ACFE estimates that healthcare organizations lose about 5% of their annual revenues to fraud—an enormous amount when applied to national health budgets (ACFE, 2020). Ghee and Button (2015) revealed that healthcare systems in 33 countries collectively lose around £299 billion annually to fraud, a figure nearly triple the UK's National Health Service annual budget. In the U.S., the National Health Care Anti-Fraud Association (NHCAA) estimated annual fraud-related losses to range between $68 billion and $230 billion (NHCAA, 2019), while Tshuma and Makhene (2024) reported that health insurance fraud in the U.S. costs approximately USD 36.3 billion annually.

In high-income countries, the scale of medical insurance fraud is well-documented due to robust data systems and consistent reporting. However, emerging evidence indicates that developing nations experience equally severe, if not more damaging, effects. In South Africa, Legotlo and Mutezo (2018) reported a case where a physiotherapist fraudulently billed over 190 consultations in one day, causing substantial financial losses. Their study estimated that fraud cost insurers about USD 145.7 annually per insured member. Across East Africa, similar trends prevail. The Insurance Outlook East Africa Report estimated that up to 25% of all insurance claims were fraudulent (Deloitte East Africa, 2020). In Kenya, precise data on the extent of medical insurance fraud remains limited due to underreporting. The IRA estimated that the industry lost approximately USD 51.36 million to fraud in 2020, with consumer fraud accounting for 21% of detected cases. These figures likely underrepresent the true extent, as weak detection systems, reputational concerns, and poor inter-agency collaboration hinder accurate reporting (Michira et al., 2021). Furthermore, the merging of medical fraud with general insurance fraud obscures specific attribution, and most insurers still rely on outdated detection methods (Salleh et al., 2018).

Despite the considerable attention to provider fraud, consumer-driven medical insurance fraud has not received equal empirical scrutiny. The literature shows that consumer fraud includes practices such as submitting claims for services not rendered, use of another individual's policy card, exaggeration of medical conditions, concealment of medical history, and acquiring multiple policies for double reimbursement (Angima & Omondi, 2016). These schemes, while often smaller in monetary terms per incident compared to provider fraud, are higher in frequency and tend to accumulate into significant aggregate losses over time (Thornton et al., 2013).

B. Forms of Consumer Medical Insurance Fraud

Medical insurance fraud typologies are unlimited and ever-changing, especially as the fraudsters, providers, and consumers, change their tactics to take advantage of system flaw. Although scholarly and regulatory attention has focused on provider fraud consisting of phantom billing and upcoding, researchers are noting that consumer-based fraud is becoming a primary cause of financial leakage in medical insurance systems. Consumer fraud is defined as a deliberate act, often through the process of claims or misreporting the eligibility or treatment information, by the policyholders or the beneficiaries to receive unjustified benefits (Villegas-Ortega, et al., 2021). In its simplest form, consumer medical insurance fraud may be divided into two general types, namely the so-called soft and the so-called hard fraud. Soft fraud manifests in the form of exaggerations or small-scale falsities embarking in otherwise valid claims like the inflated cost of medication or prolonged stay of hospitalization than those justified by medical conditions. Hard fraud, on the other hand, entails deliberate and premeditated acts of deception, such as submitting claims for non-existent procedures, faking illnesses, or colluding with service providers to fabricate entire treatment episodes (Button & Gee, 2013). These categories provide a foundational lens for understanding the underlying intent and complexity of the fraudulent behavior.

In these two wide categories, there are different sub-types of consumer fraud that have been pointed out in literature. Another familiar version is falsification of claims in which policyholders present forged documents or alter original invoices in order to obtain more than they deserve. Thornton et al. (2013) note that such a type of fraud contributes to a large percent of identified cases especially in systems that do not have in place strict document verification measures. This is common when one is charged a lesser amount on the receipts, the same receipt is sent to more than one insurer, or mischaracterization of diagnostic codes. Another important category is that of pharmacy related fraud where the person might get hold of prescription drugs by fraudulent means or alter the prescription by changing or altering the details of prescription to get higher returns as repayment. One of such methods is the acquisition of non-covered or expensive medication with the help of a valid prescription and selling it on the informal market (Salleh et al., 2018). This type of fraud occurs especially in countries that have insufficient e-prescription or consumers of pharmaceuticals which are disjointed.

Another emerging danger is that of member substitution fraud where people pose as beneficiated beneficiaries in order to avail treatment. Fraud of this form contributed to 11.3 percent of the cases of fraud in the Kenyan dataset, and it is commonly facilitated by improper identity proofing at the location of service (Angima & Omondi, 2016). There are scenarios where a single insurance card can be shared out amongst the members of a family and this happens mostly in cities with low income, where accessing healthcare facilities is not very easy and is expensive too. Research conducted by Villegas-Ortega, et al. (2021) demonstrates that the fraud of this kind is common in most developing nations, and the success of identification may depend on the use of a biometric authentication system or digital identities verification. Another form of the pernicious fraud is non-disclosure or misrepresentation of pre-existing conditions. This is at the time when they are applying or renewing the policy whereby one sets back the important medical past to escape rejections or higher premium rates. Li et al., (2008) and du Preez et al., (2025) argue that it is easy to fail to detect such fraud during underwriting process but it might become evident when the insured party attempts to lodge a claim against the insurance firm. This not only renders the claim worthless when it is found out but may also result in the abolition of the contract and a tattered image of the insurer.

Other than individual fraudsters, collusion-based consumer fraud whereby those getting the benefits are cooperating with the healthcare workers is of special harm. As an example, a patient can promise to submit fake symptoms as the provider documents an overvalued diagnosis or procedure to receive larger reimbursement. Although this has overlapping effects with that of provider frauds, the involvement of the consumer in the scheme and gain by the consumer makes this constitute consumer-driven schemes. According to ACFE (2020), schemes involving collusion cause significantly greater financial losses compared to isolated fraud, due to the systemic nature of the deception and the coordination required to evade detection. What complicates the detection and categorization of consumer medical insurance fraud is the dynamic and adaptive nature of fraud schemes. Fraudulent actors often modify their tactics to exploit new technologies, regulatory loopholes, and institutional inefficiencies. As Button and Gee (2013) argue, the increasing sophistication of fraud schemes necessitates equally advanced detection methodologies—such as data mining, artificial intelligence, and biometric verification. However, these tools remain underutilized in low- and middle-income countries due to financial constraints and limited technological infrastructure (Villegas-Ortega, et al., 2021).

C. Perpetrators and Organizational Positioning

Understanding who commits consumer medical insurance fraud—and under what organizational or situational contexts—has become essential for both theoretical advancement and policy development. Recent literature highlights that fraud perpetrators are not a homogenous group; rather, they include patients, healthcare providers, intermediaries, and internal insurance employees, all embedded in varied demographic and occupational roles across different organizational layers (Albrecht et al., 2018; Sekhon et al., 2021). Empirical research reveals that the low-level policy holders and their respective dependants are usually the most common criminals especially where little or no fraud detection system is in place, and where the claims vetting unit is understaffed or equipped (Button et al., 2008; Gee et al., 2011). These people tend to use what is called petty fraud, that is, small, repeated reimbursements based on counterfeit receipts, duplicate payment, or other unauthorized use of services (Naib et al., 2025). Furthermore, the positioning of perpetrators within the organization by their status also highly affects the possibility of occurring as well as the complexity of a fraud. As an example, intermediaries who usually have access to the system together with claims handlers are prone to engage in intricate fraud, and policyholders will seek loopholes to get out of control (Ribeiro et al., 2020). Therefore, it is important to consider how individual factors and structuring of the organizational setting interact so as to construct more effective fraud prevention and identification systems. Being modest on an individual level, the recurrence of these cases along with an overall impact on insurance companies can be devastating in a financial sense (Angima & Omondi, 2016).

However, it is not only frequency that matters. Employees within insurance companies or affiliated healthcare institutions often hold strategic positions that enable more complex and high-loss fraudulent activity. Individuals in administrative, clerical, or claims-processing roles have privileged access to sensitive information and operational systems, which they can manipulate to bypass controls or conceal their tracks. According to ACFE

(2020), the median losses from fraud committed by employees in executive or managerial roles are substantially higher than those committed by lower-tier staff. ACFE (2020) reported that executives caused losses that were more than three times greater than those by rank-and-file employees, largely due to their ability to override controls, create fictitious vendors, and approve payments without proper verification.

Beyond vertical organizational positioning, networked collusion between internal staff and external beneficiaries is a potent driver of high-impact fraud. As noted by Button and Cross (2017), many fraud schemes are not executed in isolation but involve cooperation between insiders and outsiders who share the proceeds. As an example, an insurance claims officer can help an insured party to process a fraudulent claims in return of a part of the reimbursement. Such collusive arrangements are hard to identify since they usually take place in an informal network and are camouflaged in operating regularities (Villegas-Ortega, et al., 2021). The other major dimension is a perpetrator education demographic profile. This common perception that people with a lower educational level or low income are mainly the ones who commit fraud has been clearly disapproved over and over in recent research. Manocchia et al. (2012) and Pusch and Holtfreter (2021) indicate that oftentimes highly educated individuals tend to be better at locating the loopholes in the system and creating some loopholes in the system without being caught on high-quality education, especially those who were educated in such spheres as accounting, information technology, or healthcare administration. It is noted that white-collar crimes such as insurance fraud are more likely perpetrated by individuals having the social capital, technical know-how and institutional knowledge to plan and perpetrate as well as cover complex frauds (Gottschalk 2016). These perpetrators do not just ride on failures in controls but they build sophisticated frauds that actually resemble legitimate transactions.

The last but not the least category of perpetrators is intermediaries or brokers whose involvement in the process of insurance adoption and the related privileged access to customer platforms and claim systems offers them with the opportunities of mishandling information. Although these actors are not a part of the core operation structure, in many ways they have unofficial connections with the insurers and consumers. Brokers have even been termed as having to manipulate the client documents or overcharging the premium on some cases in order to get a much higher commission or to arise phantom policies, which are then created to enable fraudulent claims (Michira et al., 2021).

D. Motivation and Behavioral Drivers of Fraud

Comprehending the driving factors that lead to medical insurance fraud is of major concern to design tailored measures, forecast models and effective regulatory rules. Fraud had previously been explained by criminological theories as caused by a position of financial desperation or deviance of an individual. Modern literature is more complex, including the aspect of psychological, social cultural, and institutional elements. The Fraud Triangle developed by Cressey (1953) is still considered a hallmark, according to which pressure, opportunity, and rationalization were essential requirements to commit fraud. Financial burden has been used as pressure in such a case as Kenya which has high out-of-pocket health expenses (Chuma & Maina, 2012). The possibility of larger losses (because the detection takes over six months) due to systemic weaknesses, such as laxity of the verification mechanisms and eventual detection of cases of frauds, create opportunities. Rationalization allows individuals to perceive fraud as justified, especially when framed against rising premiums or distrust in insurers (Gottschalk, 2016). Vousinas's (2019) Fraud Pentagon builds on this by adding capability and ego. Capability refers to the technical skills and access needed to commit and conceal fraud.

E. Relationship between Fraud Type and Financial Loss

The relationship between the type of consumer medical insurance fraud and the magnitude of financial loss is multifaceted, shaped by both structural and behavioral dynamics. While it is often assumed that complex or premeditated frauds invariably lead to greater financial harm, research indicates that this relationship is neither linear nor uniform. Empirical studies highlight that fraud type interacts with other variables—such as perpetrator access, frequency of fraud, and detection latency—to influence financial outcomes (ACFE, 2020; Villegas-Ortega, et al., 2021). For instance, "soft frauds," which involve minor misrepresentations like inflated receipts or non-disclosure of prior medical conditions, are highly frequent but individually low in value. However, these small-value schemes can aggregate into substantial cumulative losses when committed at scale and remain undetected for extended periods (Button & Gee, 2013). In contrast, “hard frauds” such as fabricated illnesses or collusion with providers tend to occur less frequently but yield significantly higher losses per incident. These schemes are premeditated and often involve multiple actors, making detection more complex and financial consequences more severe (Li et al., 2008; du Preez et al., 2025).

One of the critical mediators in the fraud type–loss magnitude relationship is the perpetrator’s capability and institutional positioning. The Fraud Pentagon Theory (Vousinas, 2019) suggests that individuals with higher technical expertise, system access, or administrative roles possess both the opportunity and capability to perpetrate sophisticated and costly fraud. This can be supported by evidence in Kenya as far as net financial losses suffered in Kenya are usually experienced when the frauds are committed by members of claims departments or people having post-secondary education (Manocchia et al., 2012). These players take advantage of internal weakness in controls making it easy to tamper with claim systems, avoid verification systems and develop fraudulent documentation with little control oversight. Further, technology has brought out different layers of fraud, which include electronic manipulation of prescriptions, duplicate billing through loopholes in the system as well as virtual consultation abuse (Thornton et al., 2013). Technologically aided frauds may take more time to attract detection in institutions with inefficient claims auditing means and institutions with a disjointed data system and this greatly increases the financial damage. Therefore, capability of the perpetrators and technology environment are crucial in predicting the financial consequences of the type of fraud determined.

F. Theoretical Framework

We adopted the Fraud Pentagon Theory and the Red Flag System Approach to explain the variables in this study. Fraud Pentagon Theory (Fraud Pentagon) was developed by Marks (2012) as a further expansion of an existing theory (Fraud Triangle) (Cressey, 1953) and Fraud Diamond (Wolfe and Hermanson, 2004), but which included an additional dimension of arrogance to pressure, opportunity, and rationalization and capability. Arrogance refers to the exaggerated feeling of invulnerability or privilege on the side of a perpetrator in the case that commonly appears in persons who think they are beyond the regulations of the institution because of them being older or more experienced, or because of having gotten away with it in the past (Marks, 2012; Situngkir & Triyanto, 2020). The advantages of this improvement on the Fraud Diamond further explain the psychological inclinations of committing a fraud especially by people who hold important or powerful positions (Soutingkir & Triyanto, 2020; Aziz & Yuniarti, 2024). All elements have distinct contributions towards the development of fraudulent conducts. The stress can be due to lack of finances, stagnation in career, or due to societal demands. Weak internal securities or loose management creates opportunity. Rationalization means that people can justify unethical behavior by using rationalizations like everybody is doing this, or I am being underpaid, among others, in the effort of aligning these acts of immorality with acceptable personal ethics. Ability enables the intruders to take advantage of systems because either they know enough to do so, or they have access to important infrastructures, and arrogance permits the intruders to do it with impunity.

The theory is especially useful in the institutional setting where structures are rigidly hierarchical, compensation is insufficient, and the problem with audit ability prevails which is typical of the insurance sector of the developing economies. As an example, claims officer/healthcare administrators can take advantage of access and knowledge to commit advanced types of fraud and rationalize this action in their view of moral disengagement or inequality. The diagnostic capability of the Fraud Pentagon is in the ability to recognize the focused solutions or interventions. Opportunity can be alleviated through effective compliance systems, pressure through ethics organizational cultures, and arrogance through frequent accountability audits, and this would be an example of systemic risk reduction strategies (Lokanan & Sharma, 2023). Therefore, the Fraud Pentagon provides a microscopic perspective to perceive and respond to fraud as a behavioral and an organizational concern.

This complementary approach that does not look at the inner motivational factors but at external displays of how institutions are likely to generate fraud comes in the form of the Red Flag System Approach. Red flags refer to patterns of behavior or institutional anomalies that signal elevated fraud risk. These include, but are not limited to, frequent overrides of internal controls, resistance to job rotation or audits, sudden lifestyle changes, irregular reporting patterns, or unexplained financial transactions (ACFE, 2020). Although these indicators are not conclusive evidence of fraud, their clustering typically precedes confirmed misconduct and should trigger investigative scrutiny.

Unlike the Fraud Pentagon, which is rooted in criminological psychology, the Red Flag System is based on behavioral economics and forensic auditing, redirecting focus from why fraud occurs to where and how it may manifest. The system emphasizes the detection of red flags—early warning indicators such as repeated overrides of authorization protocols by specific staff members—that signal behavioral clustering and potential integrity breaches (Stamler et al., 2014). Forensic auditing frameworks suggest that such behavioral red flags, including procedural overrides and bypassing internal controls, can serve as predictive variables for underlying fraudulent activity. Additionally, Dorminey et al. (2012) discuss the importance of framing the analytical lens toward the mechanisms of fraud occurrence—focusing on situational triggers and audit-relevant behaviors rather than solely motivations When paired with data analytics, red flag indicators can be encoded into digital fraud monitoring tools, allowing real-time anomaly detection in procurement, payroll, or claims systems. This diagnostic model enhances institutional capacity for early intervention and supports proactive, rather than purely reactive, fraud management strategies

The integration of the Fraud Pentagon Theory and the Red Flag System Approach allows this study to adopt a holistic lens on consumer medical insurance fraud. While the Fraud Pentagon offers an explanatory framework by identifying individual and contextual motivations behind fraud, the Red Flag System enhances detection by pinpointing behavioral and organizational signals that precede unethical conduct. The two models thus serve dual purposes: explanation and prevention. Their combined use enables institutions to not only understand the psychosocial roots of fraud but also to detect and mitigate its occurrence through robust monitoring. Ultimately, effective fraud management requires interventions that are both behaviorally informed and structurally embedded. This dual-theoretical model enables the development of adaptive, evidence-based anti-fraud strategies tailored to dynamic institutional environments.

G. Conceptual Framework.

For this study, the nature of detected consumer medical insurance fraud was the independent variable while the size of fraud losses was the dependent variable. The "nature" of fraud encompasses three key dimensions. First, fraud types include various schemes such as claim falsification, pharmacy fraud, member substitution, concealment of pre-existing conditions, and multiple policy misuse—ranging in sophistication and intent (Villegas-Ortega, et al., 2021; Thornton et al., 2013). Second, the perpetrator profile captures traits of fraudsters—policyholders, employees, or intermediaries—considering their access level, role, and capability, as framed by the Fraud Pentagon theory (Vousinas, 2019). Third, motivational factors refer to drivers like financial strain, rationalization, opportunity, ego, and collusion—elements drawn from both the Fraud Triangle and the expanded Fraud Pentagon (ACFE, 2020). These elements interact dynamically; for instance, highly capable perpetrators driven by financial need and enabled by organizational loopholes are more likely to execute complex, high-loss frauds (Pusch & Holtfreter, 2021). The dependent variable, fraud loss size, is quantified in Kenyan shillings and categorized as minor (KES 0–129,250), moderate (KES 129,251–1,000,000), and severe (>KES 1,000,000) based on IRA thresholds and internal risk metrics. This framework guides the study in linking fraud characteristics to financial impact.

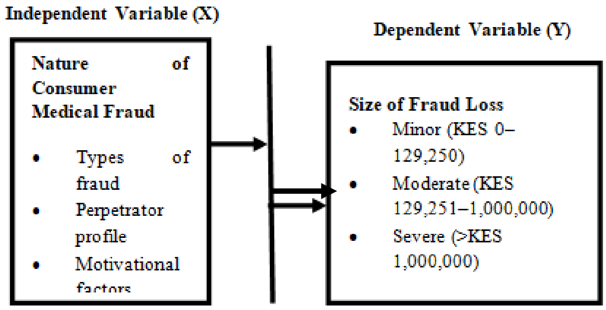

Figure 1: Conceptual framework for the study.

METHODOLOGY

This section presents the methodology adopted to conduct the study. It outlines the design, location, participants, sampling procedures, data collection techniques, data analysis, and measures for validity and reliability.

A. Design

We employed non-reactive research design to collect and analyze the secondary data on medical insurance fraud. This design uses already existing data not gathered and analyzed directly by subjects of the study (Welskop, 2022). It was best for this study because it did not subject much bias on the part of the respondents and the Hawthorne effect. It also improved validity of findings since there was no possibility that the participants would perhaps modify information because of the knowledge that they are being tested.

B. Participants

The study focused on detected cases of consumer-type medical insurance fraud among licensed medical insurance providers in Kenya. These providers comprised 21 firms, which were listed by AKI as of December 2022. Twenty-one (21) firms were contacted, 14 of them responded, which shows a response rate of 63.6% deemed sufficient for analysis. Out of these 14 companies, 53 cases of fraud cases were found and examined individually. The person was not used as a unit of analysis but each fraud case.

C. Sampling Procedure

The study used a census procedure to sample the entire observed and reported cases of consumer medical insurance fraud in a six-month duration. Such method was appropriate because the total qualifying cases were possible to cover, and the collection of more than enough data was right to have additional accuracy, reliability, and contextual generalizability (Baffour et al., 2013). Inclusion criteria included that every case of fraud detected had been detected officially where the method of detection had been captured, that a case had an investigation period of at most one month, that particulars of the perpetrator and actions taken had been recorded as well as the duration that it took to detect the fraud and the amount of money that was lost. Exclusion criteria applied to cases that lacked any of these components—for instance, where the detection method was undocumented, the investigation exceeded one month, or key data on the perpetrator or monetary loss were missing.

D. Data Collection

Data for this study was extracted from archival records and internal fraud registers maintained by medical insurance providers using a structured, coded Excel spreadsheet developed in accordance with Cheng and Phillips (2014) guidelines for secondary data analysis. The spreadsheet captured key variables including the form of fraud (e.g., claim falsification, pharmacy-related fraud, non-disclosure of ailments), type of fraudster (e.g., member, third-party, agent), amount of money lost, and the motivation and demographic details of the perpetrator. This historical data approach was both cost-effective and non-intrusive. A pilot study was first conducted at one of the medical insurance providers to assess the tool’s clarity, coherence, and operational effectiveness. Ethical approval was obtained from Dedan Kimathi University of Technology Scientific Ethics Review Committee (DeKUTSERC), NACOSTI, and participating insurance providers.

E. Analysis

The collected data was analyzed using SPSS version 28.0.0. Prior to analysis, all data were coded and cleaned to ensure internal consistency, minimize data entry errors, and conform to the requirements of statistical procedures. The measure of consumer-type medical insurance fraud and its scale was performed with the help of descriptive statistics via measuring the types of consumer-type medical insurance fraud, its frequency, and types of financial losses related to it. The chi-square tests have been used to test the relationship between the type of fraud that was identified and the value of the fraud. The method is non-parametric and is suitable to test the relationships between categorical variables and this method was apt in the fraud related variables in this study.

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RESULT

The overall aim of the given study was to discover the correlation between the character of identified consumer medical insurance fraud and the percentage scale of medical insurance fraud among providers of medical insurance in Kenya. In this part, both descriptive and inferential statistics are provided.

A. Descriptive Statistics on the Size of Detected Medical Insurance Fraud

Forms of Detected Fraud

The descriptive findings in the Table I show that the largest type of medical insurance fraud experienced among the medical insurance companies in Kenya was falsification of claims since it represented 14(26.4%) of the number of reported cases. It was then followed by pharmacy related frauds which made up 9(17.0%) of the cases. Member substitution, where one individual's information is fraudulently used by another, was the third most common form, making up 6(11.3%) of the cases. Both phantom billing and over-servicing were reported equally, each contributing 4(7.5%) of the fraud cases. Similarly, non-disclosure of prior ailments, where policyholders failed to disclose pre-existing conditions, was reported in 4(7.5%) of the cases. Generic instead of branded fraud, scripts alterations, and claim for non-covered benefits each accounted for 3(5.7%) of the cases. Servicing non-members was noted in 2(3.8%) of the cases, and merchandise substitution was the least reported form of fraud as it occurred in only 1(1.9%) of the cases.

Table I Forms of Medical Insurance Fraud

	Frequency	Percent
Pharmacy related	9	17.0
Falsification of claims	14	26.4
Phantom billing	4	7.5
Member substitution	6	11.3
Merchandise substitution	1	1.9
Generic instead of branded	3	5.7
Over servicing	4	7.5
Non-disclosure of prior ailments	4	7.5
Scripts alterations	3	5.7
Servicing non-members	2	3.8
Claim for non-covered benefits	3	5.7
Total	53	100.0

Size of Medical Insurance Fraud

The descriptive results in Table II show the extent of financial losses due to medical insurance fraud among medical insurance providers in Kenya. The majority of the reported fraud cases 20(37.7%) resulted in minor losses between Ksh 0 and Ksh 129,250. This was followed by moderate losses between Ksh 129,379 and Ksh 258,500, which represented 13(24.5%) of the cases. The category of Ksh 258,629 to Ksh 387,750 saw 7(13.2%) of the cases. Losses between Ksh 516,879 and Ksh 646,250 accounted for 6(11.3%), while those between Ksh

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387,879 and Ksh 516,000 made up 4(7.5%) of the total cases. The smaller loss ranges of Ksh 775,629 to Ksh 904,750 and Ksh 1,163,129 to Ksh 1,292,500 were reported less frequently, representing 2(3.8%) and 1(1.9%) of the cases, respectively. These results indicate that most medical insurance fraud cases result in relatively smaller financial losses, with the number of cases decreasing as the amount of loss increases.

Table II Amount Lost Amount of Money Lost to Medical Insurance Fraud

Amount Lost (Ksh)	**Frequency**	**Percent**
0 - 129,250	20	37.7
129,379 - 258,500	13	24.5
258,629 - 387,750	7	13.2
387,879 - 516,000	4	7.5
516,879 - 646,250	6	11.3
775,629 - 904,750	2	3.8
1,163,129 - 1,292,500	1	1.9
Total	**53**	**100.0**

Descriptive Statistics for Nature of Detected Medical Insurance Fraud

Table III presents the distribution of different types of medical insurance fraudsters in the detected cases. The distribution indicates that health service providers were the most common perpetrators of fraud as they comprised over half of the cases at 30(56.6%). Members or beneficiaries were involved in slightly more than a third of the cases 20(37.7%). Brokers or agents were the least frequent perpetrators involved in only 2(3.8%), while third-party administrators accounted for 1(1.9%). These findings indicate that the majority of medical insurance fraud was committed by health service providers and members/beneficiaries.

Table III Frequency Distribution for Type of Medical Insurance Fraudsters in the Detected Cases

	Frequency	Percent
Health service provider	30	56.6
Member/beneficiary	20	37.7
Broker/Agent	2	3.8
Third party administrators	1	1.9
Total	53	100.0

Table IV further presents the distribution of the detected medical fraud cases based on the designation of the perpetrators within the organizations. The data shows that the majority of detected fraud cases were committed by individuals in non-management positions as indicated by 32(60.4%) of the total cases. Management-level employees were responsible for 14(26.4%) of the fraud cases. Executives were involved in 7(13.2%) of the cases and this represented the smallest proportion of detected fraud perpetrators. This suggests that lower-level employees are more frequently involved in fraud within these organizations. While management plays a significant role in these organizations, they are less frequently implicated in fraud compared to non-management staff.

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Table IV Frequency Distribution for Designation of the Medical Fraud Perpetrators in the Detected Cases

	Frequency	Percent
Executive	7	13.2
Management	14	26.4
Non-Management	32	60.4
Total	53	100.0

Chi-Square Test for Type of Medical Insurance Fraudsters and Size of Medical Insurance Fraud

A chi-square test (χ^2) was conducted to assess whether there was a relationship between the type of medical insurance fraudsters and the size of medical insurance fraud among insurance providers in Kenya. The results presented in Table V show that there was no statistically significant association between the type of medical insurance fraudsters and the size of the fraud, χ^2 (18, N = 53) = 18.752, p = .407. This result implies that the variation in the size of medical insurance fraud is not significantly associated with the type of fraudster involved. Furthermore, the likelihood ratio test also indicated a lack of significant association, χ^2 (18, N = 53) = 15.799, p = .607. It worth noting that 25 cells (89.3%) have an expected number of less than 5; the expected less number is .02. It is against the assumption of the chi-square test because a cell is expected to have 5 or more expected counts in order to produce dependable results. This indicates that perhaps the sample size was too low to find a substantial connection, and the data distribution within the groups of fraudsters was not normalized, and this fact may have had the ability to influence the findings.

Table V Chi-square Test for Type of Medical Insurance Fraudsters and Size of Medical Insurance Fraud

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	18.752[a]	18	.407
Likelihood Ratio	15.799	18	.607
Linear-by-Linear Association	.663	1	.416
N of Valid Cases	53		
a. 25 cells (89.3%) have expected count less than 5. The minimum expected count is .02.			

Chi-Square Test for Designation of the Medical Fraud Perpetrator and Size of Medical Insurance Fraud

To analyze this correlation, a chi-square test was carried out to analyze the relationship involving the designation of the perpetrators of medical fraud and size of the detected medical insurance fraud among the insurance providers in Kenya. The findings tabulated in Table VI reveal that the association that existed between the designation of the medical fraud perpetrators and the magnitude of the fraud was statistically significant, 2 (12, N = 53) = 22.050, p = .037. This significant result suggests that the size of medical insurance fraud was related to the role or designation of the fraud perpetrator. However, it is important to note that 18 cells (85.7%) had an expected count of less than 5, with the minimum expected count being .13. This finding points to a potential issue with the validity of the chi-square test results, as the chi-square test assumes that the expected count in each cell should be 5 or more for reliable results. The small expected counts might have introduced bias or reduced the reliability of the test. The likelihood ratio test, which provides an alternative assessment of the association between variables, yielded a non-significant result, χ^2 (12, N = 53) = 19.884, p = .069, indicating a lack of strong evidence for the association when considering the likelihood ratios.

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Table VI Chi-Square Test for Designation of the Medical Fraud Perpetrator and Size of Medical Insurance Fraud

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	22.050[a]	12	.037
Likelihood Ratio	19.884	12	.069
Linear-by-Linear Association	7.301	1	.007
N of Valid Cases	53		
a. 18 cells (85.7%) have expected count less than 5. The minimum expected count is .13.			

Chi-Square Test for Form of the Detected Medical Insurance Fraud and Size of Medical Insurance Fraud.

A chi-square test (χ^2) was conducted to evaluate whether there was a relationship between the form of the detected medical insurance fraud and the size of the fraud among insurance providers in Kenya. The results presented in Table VII indicate that there was no statistically significant association between the form of the detected medical insurance fraud and the size of the fraud, χ^2 (60, N = 53) = 45.570, p = .916. This suggests that the variation in the size of medical insurance fraud is not significantly related to the form of fraud detected. In addition, the likelihood ratio test further supports this finding, showing no significant association, χ^2 (60, N = 53) = 47.192, p = .885. It is also crucial to note that 76 cells (98.7%) had an expected count of less than 5, with the minimum expected count being .02. This again violates the assumption of the chi-square test that expected counts should be 5 or more in each cell for reliable results. Therefore, the results should be interpreted with caution.

Table VII Chi-Square Test for Form of the Detected Medical Insurance Fraud and Size of Medical Insurance Fraud

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	45.570[a]	60	.916
Likelihood Ratio	47.192	60	.885
Linear-by-Linear Association	5.256	1	.022
N of Valid Cases	53		
a. 76 cells (98.7%) have expected count less than 5. The minimum expected count is .02.			

DISCUSSION

The findings of this study affirm the multidimensionality of consumer-type medical insurance fraud in Kenya, with falsification of claims emerging as the most dominant scheme. This aligns with global and regional literature highlighting falsified claims as a recurring modality, particularly in environments with weak verification infrastructure (Li et al., 2008; du Preez et al., 2025; Thornton et al., 2013). The recurrence of pharmacy-related fraud and member substitution, accounting for 17.0% and 11.3% respectively, corroborates Legotlo and Mutezo (2018) and Villegas-Ortega, et al. (2021), who emphasize the vulnerabilities within pharmaceutical dispensation systems and identity verification protocols in low- and middle-income countries. These typologies indicate that the Kenyan fraud topography, although being synonymous with global trend has local characteristics that are determined by the inabilities of its administration, economic strains and poor biometric-based verification infrastructure. For instance, member substitution, often facilitated by weak identity management at service points, suggests gaps in enforcement that fraudsters exploit. The implications are

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twofold: first, the absence of real-time identity validation systems increases systemic exposure, and second, claims falsification thrives due to limited capacity for cross-verifying claims with medical records.

From a financial standpoint, the analysis indicates that the majority of fraud cases led to minor losses ranging between Ksh 0–129,250 (37.7%), while moderate losses (Ksh 129,379–258,500) constituted 24.5%. These results align with findings by the ACFE (2020) and Dyck et al. (2024), who observe that although high-value frauds receive disproportionate attention, low-value, high-frequency frauds accumulate substantial aggregate losses. The Kenyan case reflects this global trend but reveals a context-specific dynamic: most frauds remain below Ksh 646,250, suggesting a prevalence of opportunistic rather than organized fraud schemes. This observation contrasts with highly developed insurance markets such as the U.S., where high-value and often collusive frauds dominate (Ghee & Button, 2015). The difference is likely attributable to structural and economic factors—developed markets exhibit higher insurance penetration, mature fraud analytics infrastructure, and a more formalized health economy. In contrast, Kenya's fragmented health infrastructure, reliance on manual claims vetting, and limited actuarial oversight foster an ecosystem where frequent, small-scale frauds can thrive with minimal risk of detection.

The findings on the types of perpetrators and their organizational designation provide further nuance to the fraud ecology in Kenya. Notably, 56.6% of fraud cases were perpetrated by health service providers, while members accounted for 37.7%. These proportions affirm prior studies (Angima & Omondi, 2016; Michira et al., 2021) that underscore the duality of fraud sources—internal and external. However, what distinguishes this study is the granularity of perpetrator roles, with non-management employees accounting for 60.4% of detected frauds. This supports the ACFE (2020) observation that while executive-level frauds are financially severe, rank-and-file employees account for the bulk of case volume. This pattern may reflect ease of access to operational loopholes by lower-level staff, who often serve as gatekeepers to documentation and claims systems. Furthermore, this supports the Fraud Pentagon Theory (Vousinas, 2019), which highlights "capability"—the perpetrator's ability to exploit systemic weaknesses—as central to fraud execution. Non-management staff, though not wielding organizational authority, may be best positioned to exploit routine procedural vulnerabilities, especially where oversight mechanisms are lax or accountability protocols underdeveloped.

Statistical inference from the chi-square tests added insight into the dynamics between fraud characteristics and financial loss. The lack of a significant association between fraud type and financial loss contradicts prior findings in international literature (Li et al., 2008; ACFE, 2020), where specific types—like collusion or document forgery—were consistently associated with higher losses. In this study, the absence of such association may stem from sample limitations and data distribution imbalances, as suggested by the high frequency of cells with expected counts below five. Despite this methodological constraint, the finding hints at a more egalitarian distribution of financial loss across fraud types in Kenya, possibly reflecting institutional homogeneity in detection capacity across providers. However, one statistically significant relationship was observed: the designation of the fraud perpetrator correlated with the size of the fraud (χ^2 (12, N = 53) = 22.050, p = .037). This confirms literature by Vousinas (2019) and Manocchia et al. (2012), which posits that frauds perpetrated by individuals with higher organizational access tend to result in greater financial losses due to the breadth of their operational control and ability to override controls.

This designation-based correlation is also valid as empirical back-up of theoretical claims inherent in the Red Flag System Approach, which concerns itself with anomalous behavioral patterns within certain levels of the organization. Executives and management-level employees, though less frequently implicated (13.2% and 26.4%, respectively), were more likely to be involved in high-value frauds. Their access to approval systems, minimal supervision, and discretionary authority over claims processes create an environment where internal checks are insufficient to prevent manipulation. Gottschalk (2016) and Pusch and Holtfreter (2021) further supports this, noting that high-ranking individuals often design fraud schemes that mimic legitimate operations, making detection complex and delayed. This underscores the importance of instituting hierarchical rotation policies, continuous auditing, and digital surveillance mechanisms—especially at senior levels. From a prevention standpoint, these findings suggest that organizational control environments need to be stratified, with stricter protocols for senior personnel. As highlighted in the Fraud Pentagon's "arrogance" dimension, high-level actors may perceive themselves as untouchable, and only robust accountability mechanisms can mitigate such hubris.

The study also draws attention to understudied forms of fraud in the Kenyan context—such as non-disclosure of prior ailments and over-servicing—which each comprised 7.5% of the cases. These forms are often downplayed in global discourse in favor of provider-centric fraud typologies like phantom billing or upcoding (Villegas-Ortega, et al., 2021). However, in resource-constrained settings, the economic impact of such "soft frauds" is nontrivial. These schemes often escape detection due to their low monetary profile per incident and their embeddedness in legitimate transactions. However, as Thornton et al. (2013) accentuate when perpetuated with a commitment and unobserved, they cause high cumulative financial leakage. They are present in Kenya as a result of the specificity of the sociocultural environment and consumer behavior, where the out-of-pocket cost of healthcare prompts an insured individual to ride the edges of his or her insurance. This also resonates with Chuma & Maina's (2012) findings on healthcare financing in Kenya, which attribute such behaviors to economic survival strategies in a largely informal economy. Policy solutions therefore need to extend beyond punitive systems and include consumer education, awareness campaigns and incentivized system of transparent, obscurer.

In synthesizing these findings through the lens of the study's dual-theoretical framework, it becomes evident that both individual behavioral traits and systemic vulnerabilities interact dynamically to produce fraud outcomes. The Fraud Pentagon explains the inner logic of those committing fraud; pressure, rationalization and so on, whereas the Red Flag System brings anomalies in institutional behavior into the foreground, because these are observable. For instance, the statistical finding that executive-level frauds tend to be of higher financial magnitude can be interpreted as a convergence of "capability" and "arrogance," two critical tenets of the Pentagon model. Simultaneously, the failure of organizations to detect these frauds early enough reflects a weakness in red flag identification. The study thus validates the integrative use of behavioral and structural models to understand fraud not as isolated acts but as organizationally situated phenomena. This calls for a dual-pronged fraud management strategy—strengthening institutional detection systems while addressing the psychological drivers of fraud. It further supports Button and Cross's (2017) call for transitioning from reactive to predictive fraud management approaches, especially in vulnerable health financing systems.

Limitations

This study faced several methodological and contextual limitations that must be acknowledged. First, gaining access to fraud-related data from medical insurance providers proved difficult. Due to the sensitive and reputationally risky nature of insurance fraud, some firms were reluctant to share internal records. Although the research team mitigated this concern through formal confidentiality agreements and ethical clearance, the resulting sample may underrepresent organizations with stricter data disclosure policies. Second, the reliance on archival records limited the comprehensiveness of the dataset. Only detected and documented cases were analyzed, excluding undetected or unreported fraud. This constrains the study's capacity to estimate the full prevalence and economic impact of consumer medical insurance fraud in Kenya. Moreover, because the data were non-reactively collected, their structure and completeness were beyond the researcher's control.

Third, historical inconsistencies in documentation led to missing or incomplete information. To ensure data integrity, strict inclusion criteria were applied, which may have further narrowed the sample size and reduced statistical power. Finally, the findings are context-specific and not fully generalizable. Only 14 out of 21 eligible insurers participated, potentially introducing selection bias. Finally, the study's cross-sectional and observational design precludes causal inference. While associations between variables were statistically explored, temporal or mechanistic causality cannot be conclusively established.

CONCLUSION

This study investigated the relationship between the nature of detected consumer-type medical insurance fraud and the size of associated financial losses among medical insurance providers in Kenya. The findings underscore the multifaceted nature of consumer-driven fraud, revealing that while falsification of claims is the most frequently detected scheme, it is not necessarily the most financially damaging. Other fraud forms—such as submitting claims for non-covered benefits or servicing non-members—though less common, were often linked with higher loss values. This suggests that fraud frequency alone does not predict financial severity, reinforcing the theoretical insights from the Fraud Pentagon, which emphasizes capability and opportunity as critical determinants of fraud magnitude (Vousinas, 2019). Moreover, the study's statistically significant association between the perpetrator's organizational designation and loss size confirms that frauds committed by individuals in higher-ranking roles tend to inflict greater financial harm, likely due to their system access and ability to override controls. These findings highlight the need for Kenyan insurers to adopt nuanced fraud detection strategies that prioritize not just frequent fraud types, but those with high financial impact, even if rare.

While the study makes an important empirical contribution by focusing exclusively on consumer-type fraud in a Kenyan context, its findings also invite broader reflections for future research and policy. The exclusive focus on detected cases implies that undetected or misclassified frauds remain beyond empirical reach, potentially underestimating the full scope of loss. Additionally, the cross-sectional, archival design limits causal inference, though it offers valuable associative insights. Going forward, research should consider expanding the analytical lens to include provider-initiated and intermediary frauds, which may reveal different dynamics in fraud structure and financial consequences. Institutional-level variables—such as internal audit capacity, digital claims infrastructure, and fraud reporting culture—were not accounted for in this study but are likely influential. Mixed-methods research incorporating organizational case studies and qualitative interviews with fraud investigators could illuminate these dimensions. Furthermore, contextual factors such as macroeconomic stress, insurance literacy, and regulatory stringency—known to shape fraud behavior—should be integrated into future statistical models to enhance explanatory power. Ultimately, fraud in medical insurance is not merely a technical challenge, but a socio-economic and organizational phenomenon. Addressing it effectively will require interdisciplinary approaches that combine behavioral theory, institutional reform, and predictive analytics.

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