Harnessing Machine Learning and Artificial Intelligence for Early Fraud Detection Among Banks in Harare, Zimbabwe: Internal Auditors' Perspective

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Abstract

https://doi.org/10.34047/MMR.2024.111

The study explores the transformative power of utilizing machine learning and artificial intelligence for early fraud detection among banks in Harare, Zimbabwe using qualitative research. Data were collected through document reviews and in-depth interviews with bank internal auditors and senior management. The study addressed three key research questions, namely, examining internal auditors' understanding of machine learning and artificial intelligence tools/systems for fraud detection; understanding internal auditors' perceptions on the effectiveness of machine learning and artificial intelligence-based fraud detection systems; and identifying major challenges faced by internal auditors during implementation of artificial intelligence fraud detection systems. Internal auditors' perceptions were gathered through in-depth interviews which were conducted face to face and online. Findings from the study demonstrated strong consensus among internal auditors on the potential power of machine learning and artificial intelligence in detecting fraud at an early stage. In addition, the study revealed the potential benefits of utilizing machine learning algorithms and artificial intelligence which includes enhanced speed in identifying anomalies, improved accuracy, and the ability to detect fraud early, thereby enabling management to come up with internal control mechanisms which can prevent fraud. Successful implementation of machine learning and artificial intelligence-powered fraud detection systems require adequate training and support from the organization's leadership, and ethical considerations.

Keywords: Artificial Intelligence, Machine Learning, Fraud Detection, Internal Auditors

I. Introduction

Banks play a crucial role in any economy as they enhance economic growth and stability of nations worldwide. However, these banks have been a target of fraudulent activities since time immemorial because they house most precious and liquid assets such as cash and gold. The increasing rise of advanced technologies and use of the internet for operational purposes by banks and the transacting public has brought in advantages both to the bank and the customer, such as banks offering tailor made services to clients, cost reduction and development of new business models (Bredt, 2019). However, the same technology has brought in sophisticated ways of committing fraudulent activities by fraudsters as they manipulate the banking system leading to significant financial losses and reputational damage for the bank. To deal with this risk, financial institutions are exploring innovative and sophisticated approaches to ensure their fraud detection capabilities are enhanced. Recently, one such approach is integration of Machine Learning (ML) and Artificial Intelligence (AI) tools in the operational framework of the bank.

AI is changing how businesses are run worldwide. It is enabling institutions to automate their day to day processes, improving customer experiences and enhancing operational efficiency and is applied in different sectors of the economy including medical diagnostics, optical character recognition, automotive autonomous driving and financial services (Bredt, 2019). Key tasks such as customer services, risk assessment, trading and fraud detection are slowly being delegated to AI-powered systems (Goodell, et al., 2021). AI technologies are so powerful that they can analyze large quantities of data in a short space of time and can also quickly detect anomalies, hence this can enhance early detection of fraudulent activities. Globally, AI in the banking sector is gaining momentum and will have an accelerated impact on financial services (Accenture, 2021; Bredt, 2019), as banks are leveraging on AI tools to streamline their operations, personalize customer experience and strengthen their risk management frameworks. Internal auditors are a key ingredient in maintaining the integrity of financial systems within banks and traditionally they have relied on manual processes and basic data analytics to detect and predict potential fraud. However, the prevalence of technology has brought about sophisticated fraudulent activities that has necessitated adoption of advanced technology such as AI to enhance efficiency and effectiveness of audit processes.

ML continues to grow pervasively within job categories (Brynjolfsson, et al., 2018), and the internal audit profession is not an exception as tasks such as reconciliations, report writing and fraud detection can be assigned to AI tools. In order to efficiently adodpt AI in the workplace Brynjolfsson, et al (2018) advocates the redesign of jobs and reengineering of business processes. Banks in Zimbabwe embraced mobile banking for over two decades but the extent of using AI in fraud detection is not known. How has been the transformative power of utilizing machine learning and artificial intelligence for early fraud detection among banks in Harare, Zimbabwe? How have auditors embraced this technological shift? These are the overarching issues addressed in this study.

Emergence of AI dates back to the mid-20th centuries, during that time it was just a scientific discipline. The term AI was originated at the Dartmouth Conference, when a group of researchers gathered to discuss and explore ways of making machines that can emulate human thinking (McCarthy, et al., 1955). By that time progress was slow because of limited resources in terms of computing power as compared to the complexity of human intelligence. Fast forward to the 21st century there was a resurgence of AI, and this time around it was pervasive and driven by several factors. AI is now integrated in our everyday lives as it can be witnessed in almost all industries such as healthcare, agriculture, transport, finance and education. The improvement of AI is now exponential and its impact is nothing to ignore. The auditing profession is an anchor in organizations because auditors are in a position of ratifying on the trustworthiness of financial statements and operations of the organization, thereby influencing the operations of capital markets. As technology is emerging it also means that sophisticated forms of committing acts of fraud also improves, this therefore leaves auditors with no option but to embrace adoption of AI in their day to day activities. AI can not necessarily replace the human auditor but can augment and enhance the efficiency of the auditor and ultimately improve operational efficiencies and quality of financial reports. It is against this background that a study to explore the power of AI in early fraud detection be undertaken.

I.I Research Questions

- What are the internal auditors' understanding of machine learning and artificial intelligence tools/systems for fraud detection among banks in Harare, Zimbabwe?

- What are the internal auditors' perceptions on the effectiveness of machine learning and artificial intelligence-based fraud detection systems among banks in Harare, Zimbabwe?
- What are the challenges faced by internal auditors during implementation of artificial intelligence fraud detection systems among banks in Harare, Zimbabwe?

This paper is organized into five sections. Section 1 presents the introduction and research questions to be addressed. Literature review and theoretical framework are covered in section 2. Section 3 provides the research methodology employed by the study while section 4 presents discussion of the research findings. Conclusion and recommendations emanating from the study are presented in section 5.

2. Literature Review

2.1 Theoretical Framework

Three theories were adopted as a basis for guiding this study and these are Technology Acceptance Model (TAM), Institutional Theory and Technology Organization Environment (TOE). TAM proposed by Davis (1989) and later on extended by Venkatesh and Davis (2000), this theory focuses on individual acceptance and adoption of new technologies. The theory suggests that users attitudes and intentions to use technology are influenced by perceived usefulness and perceived ease of use. TAM is useful in this study because it guides us in understanding internal auditors' perceptions, familiarity and understanding of ML and AI-tools for early fraud detection, therefore TAM provides insights into internal auditors' potential acceptance and likelihood of use of ML and AI.

Institutional theory has been developed by various scholars over time, these include Meyer and Rowan (1977), DiMaggio and Powell (1983), and Scott (1995), It looks at the influence of social and organizational structures on individuals' behaviors and actions, It propounds that institutions and their members are influenced by external pressures, norms and expectations the institution's environment and these factors shape the individual's beliefs, behaviors and practices within the organization. This theory was adopted in this study because it helps in understanding how the institutional environment in Zimbabwe's banking sector shapes auditor perceptions and behaviours related to ML and AI-based fraud detection systems.

The Technology Organisation Environment framework was initially proposed by Tornatzky and Fleischer (1990) and later on refined by Zhu, et al. (2006), this framework focuses on technological innovations in organizations and considers three major dimensions as follows: technological factors, organizational factors and environmental factors. This framework enhances understanding of the technological capabilities required in implementing ML and AI-based systems, as well as assessing the readiness of organizations to adopt these systems taking into account the influence of the external environment. Adopting this theory assists in analyzing critical success factors and challenges faced by internal auditors during the process of implementing ML and AI-based fraud detection systems.

2.2 Artificial Intelligence and Machine Learning

AI is a collection of different technologies working collectively to empower machines to mimic human-like levels of intelligence (Russell & Norvig, 2016; Accenture, 2023). Shambira (2020), defines AI as a theory and development of computer systems which have capabilities to undertake tasks that usually require human intelligence, such tasks include visual perception, speech recognition, decision making and language translation. On the other hand ML is a subfield of AI which studies ways of building computer programs that automatically improves performance tasks through experience without explicit programming (Mitchell, 1997; Brynjolfsson, et al., 2018).

AI encompasses ML as its major key component and because of that AI and ML are often used interchangeably (McCarthy et al., 1955), However some authors draw clear lines between the two aspects and places ML as a broader field of AI (Goodfellow et al., 2016). This interchangeability can have implications for insinuating the capabilities and scope of AI and ML within the financial services sector. In the banking sector AI-powered chatbots and virtual assistants have become so prevalent, these expert systems utilize Natural Language Processing (NLP) and ML algorithms to converse with clients, respond to queries, provide support and perform basic transactions (Bank of America, 2020). With regard to banking and auditing, AI and ML offer many possibilities for improving efficiency, accuracy and enhanced decision making process, as auditors can automate data analysis in identifying audit risk and detection of anomalies in operations (KPMG, 2023). Moreover, AI-powered systems can help organizations improve customer experience in many ways such as reduced response time and personalizing financial services (The Economist, 2020; Lui & Lamb, 2018).

Buchanan (2019) show that AI is significantly changing the financial services sector in following four major ways:

Fraud detection: Since the emergence of e-commerce there has been widespread occurrence of online fraud, hence use of AI is likely to eliminate criminal funds from the system.

Banking chatbots and robot-advisors: ML algorithms can be trained on large quantities of customer data, thereby helping clients manage their money and savings.

Algorithmic trading: Use of AI for making trading decisions requires complex AI systems, algorithmic trading has the noble advantage of making quick trading decisions taking advantage of the limited profitable opportunities in the market.

Regulation and policy: AI and markets are becoming more complex by the day, thereby presenting some major challenges regarding regulation and policy making.

2.3 Artificial Intelligence & Machine Learning in Internal Auditing

Internal auditing is a critical department which plays a crucial role in the detection and prevention of fraud (Kahyaoglu & Aksoy, 2021), therefore in order to further enhance early fraud detection in banks there is need to adopt AI tools in the banking sector (Buchanan, 2019). The emergence of expert systems such as AI and machine learning tools is promising to curb the implications of delayed fraud detection and prevention as internal auditors can now automate audit and risk control processes in banks (Couceiro, et al., 2020). Many studies (Singh & Pathak, 2020); Kahyaoglu & Aksoy, 2021; Buchanan, 2019; Couceiro, et al., 2020) are being undertaken to examine the effect of AI in organizations, for example trying to understand internal auditors' familiarity and understanding of the emergence and operational effectiveness of AI and ML technologies. Shimamoto (2022) notes that auditors should embrace technology as much as they can and familiarize themselves with ML and AI techniques, because of this proper training and education for internal auditors should be prioritized to enhance internal auditors' skills and knowledge of AI and ML tools usage. Moreover, auditors need to understand the underlying principles of AI and ML tools in leveraging their potential for fraud detection and prevention, this therefore places internal auditors in a critical position of understanding and following AI trends and development over time.

AI powered fraud detection tools have the advantage of providing a more comprehensive understanding of risks that emanates from various transactions and customer behavior. This is because of the sophisticated power of machine learning. Since banks deal with vast quantities of data and information including customer profiles, transactional history and other external factors such as regulation, AI can assist internal auditors to quickly identify high risk activities and flag them for further investigations. This therefore enables internal auditors' priorities their efforts in other strategic areas, thereby adding value to the organization. However, care should also be taken by internal auditors as they adopt and utilize AI technologies in their work, because as it stands most of these AI tools still have a lot to learn in terms of operational systems. Management in conjunction with internal auditors should come up with a sustainable AI implementation framework which ensures that all the likely risks which comes from use of AI are safeguarded, therefore total delegation of AI technologies to perform all tasks is not recommended (Popenici & Kerr, 2017). Human auditors are still relevant to augment the efficiencies brought in by AI. Internal auditors should therefore always seek ways through their various professional bodies to capacitate themselves with AI skills so that they can continue to be relevant in their departments.

Since the emergence of AI and ML and their use in detection of anomalies, there has been mixed discoveries by scholars regarding effectiveness of these expert systems in fraud detection, In this regard Noor & Mansor (2019) finds that AI and ML tools significantly outperform traditional rule based approaches to fraud detection in organizational operations, and this shows that AI and ML based systems bring benefits of quick detection of fraudulent activities in organizations. On the other hand a study by Lui & Lamb (2018) notes concerns of false positives, whereby AI and ML systems can wrongly diagnose fraud when in actual fact there is no fraud, this therefore calls for continuous monitoring and refining of these AL and ML tools by systems developers together with end users such as internal auditors.

Adoption of AI and ML systems for fraud detection brings with itself various challenges on internal auditors, one issue has to do with lack of technical expertise, resistance to change and data quality issues and an inability to document use of technology in their audit methodologies (Seethamraju & Hecimovic, 2020). This then calls for management to come up with measures such as crafting policies which clearly articulate their vision and show of support on the adoption of AI and ML tools as fraud detection tools (Buchanan, 2019). Moreover Lui & Lamb (2018) finds that the transition period can be faced with hurdles in terms of integrating AI and ML tools into existing auditing processes so that the two systems can be integrated as they run parallel, in order to deal with a problem of this kind management and those charged with governance should at least continue to capacitate the internal auditing department with resources so that they can acquire skills and emerging methodologies which can accommodate the new technologies effectively, also there is need for strong collaboration between internal auditors and the IT department to guarantee smooth integration and transition of AI technologies into the existing infrastructure (Lui & Lamb, 2018).

The detection and predictive capabilities of AI and ML tools seem to be limited in scope, for example Buchanan (2019) notes that there have been several scenarios were the algorithms implemented by financial services firms acted in totally unexpected ways during financial crisis periods, leading to errors and financial losses. Therefore, internal auditors in banks should take some precaution when they decide to entirely automate their fraud detection systems because the consequencies of

AIand ML errors can be dire.

Internal auditors are afraid that full automation of their roles could lead to their replacement, especially the introduction of ML and AL (Alina & Cerasela, 2018). In the same vein Hasan (2022) also warns that because of the introduction of ML and AI it is highly certain that traditional jobs will dissapear. Given internal auditors' fears and genuine concerns of full automation, they should try to be pro-active and find ways to enhance their skills so that they can augment AI tools and add value in their organisation, for example they can choose to focus their attention on issues of ethics, improvement of internal controls, risk management and governance.

Although banks in Zimbabwe have been using digital banking platforms including mobile banking, the extent of AI use is unknown (Shambira, 2020). An interesting study by Singh & Pathak (2020), finds that increased use of AI in the Indian Banking system led to customers making more use of digital banking platforms because of the user friendly experiences brought about by AI use.

2.4 Artificial Intelligence and Machine Learning in the Banking Sector

The banking sector continues to witness significant advances in technology as the adoption of AI tools such as robots and chatbots is getting increasingly popular (Lui & Lamb, 2018). In the near future AI has the potential of becoming a central innovation driver in the financial services industry even though it is not yet clear what the future financial services industry would look like. AI and ML technologies enable banks to analyze large volumes of data, identify patterns and anomalies that may show fraudulent activities (Ris, et al, 2020). A study by Noreen, et al (2023) finds that some banks are using AI and ML tools for risk assessment, customer services, credit scoring and personalized financial recommendations. Using AI and ML tools this way can ultimately lead to enhanced operational efficiency and effectiveness.

A report by Deloitte (2018) shows that 76 percent of chief executive officers in the banking sector agree that AI is critical and should be top priority because it is a critical differentiating factor. In Zimbabwe AI is slowly getting traction and acceptance despite facing some hurdles, in this regard drivers to AI adoption in the Zimbabwean banking sector are customer satisfaction, cost reduction and the need to improve risk management. However, lack of resources including AI experts, lack of AI knowledge in general, data privacy and security issues have been cited as barriers to AI adoption (Shambira, 2020).

Evidence on ML algorithms show that AI use in the banking sector could lead to discrimination against certain races and gender (Lui & Lamb, 2018; Johnson, et al., 2019), therefore as AI adoption is being undertaken there is need for a holistic and interdisciplinary approach to AI regulation to avoid any negeative connotations that may come with AI adoption (Hasan, 2022), regulatory authorities should even consider mandating all institutions adopting AI use to have an established ethics committee that from time to time monitor the bahavior of AI towards such sensitive issues as gender and race (Fukas, et al., 2021). Moreover in the same vein Buchanan (2019) mentions that there are concerns, uncertainties and risks that still need to be addressed as AI is still in its early stages of adoption such concerns and issues include legal consequencies resulting from AI use, ethical issues, economic and social issues. All this shows that even though AI adoption may lead to positive disruptions in the financial services industry, still more need to be done to have a conducive operational environment for harnessing AI in organisations.

AI in Zimbabwean banks can be significantly accelerated if the Reserve Bank of Zimbabwe (RBZ) as a regulator of banks realise the need to take advantage of opportunities for enhanced compliance and safety (Wall, 2018). Internal auditors in Zimbabwe are likely not to worry themselves in adopting AI and ML tools for fraud detection as long as the supervisor (RBZ) is not taking up an active role to push for AI use in banks fraud detection systems. Shambira (2020) observed that banks' reluctance to embrace AI in early fraud detection was due to lack of resources and expertise.

3. Research Methodology

The study used qualitative approach (Bryman, 2001). The study was aimed at understanding perceptions of auditors on the potential of artificial intelligence and machine learning in early fraud detention. The population of the study included all banks in Harare. The City of Harare was purposively selected., hence qualitative methodologies were adopted. Document reviews and in-depth interviews were used to gather data. The use of in-depth interviews was important in seeking further clarity. Both face to face and online interviews were conducted. Face to face interviews were important as non-verbal cues would be picked up as relevant information. Online interviews were mainly for convenience, and from the 10 interviews conducted 3 were done online. Purposive sampling was used, and only internal auditors were interviewed. Data saturation was reached at the 10^{th} interview and interviews were immediately stopped. In terms of trustworthiness, interviews were triangulated as researchers were part of the interviews to ensure that no researcher would alter data. Participation in the study was voluntary. Thematic analysis was used in data analysis.

4. Discussion of Research Findings

4.1 Internal auditors' understanding of ML and AI tools/systems for fraud detection

The study found that there is a disparity between use of artificial intelligence in terms of two factors. The first factor is about age, as older internal auditors showed that they are not familiar with and showed resentment to ML and AI tools and younger internal auditors showed strong familiarity and confirmed that they are using these tools. For example, P5 said: "These AI and ML tools are not for us old people but I have seen young employees using them frequently in fraud identification." The other factor was on nature of bank. Banks that are owned by the government (parastatals) indicated that they are not using ML and AI tools for early fraud detection. For example, P2 from a parastatal bank said "Our bank has not been given permission by the government to use AI and ML in any activity." However, the study found that privately owned banks which are less rigid are using chatbots such as REVE chat, Shield, Actico and iComply. This slightly contradicts with findings from a study by Shambira (2020) which finds that only 16 percent of banks in Zimbabwe have adopted some form of AI such as chatbots to enhance customer satisfaction and experience.

4.2 Internal auditors' perceptions on the effectiveness of ML and AI-based fraud detection systems

The second research question was on internal auditors' perceptions on the effectiveness of ML and AI-based fraud detection systems. In terms of perceptions on effectiveness of ML and AI-based fraud detection systems, three themes were established. The major benefit of ML and AI tools is that there is speed in identification of anomalies. The study found that ML and AI is quick in identifying fraud and the bank is warned without incurring many costs. This is echoed by P1 in these terms, "You can't compare AI and a human being, AI immediately detects fraud………By the time a human being detects fraud the bank would have lost a lot of money." This finding concurs with Noreen et al (2020) in the UK who submit similar findings. The other perceived benefit is on improved accuracy. This was substantiated by P7 who submitted that “AI and ML tools are accurate in fraud detection, us as humans at times we raise false alarms which can be costly, and this is not the case with these technologies.” This is similar to Shambira (2020) findings in Zimbabwe that AI and ML are accurate than humans.

In addition, the study found that ML and AI tools reduce costs. This usually has to do with costs associated with hiring many employees to detect fraud. A single AI tool can do the job for more than 50 people. With the use of ML and AI, it means the organisation has to cut its auditing department costs. This is what P6 said on this “Some of the costs that make banks not profitable are human resources because they are recurring costs, with AI and ML you can trim down your human resources because you no longer need them.” This converges with Sing & Pathak (2020) that AI and ML reduces labour related costs.

4.3 Challenges faced by internal auditors during implementation of AI fraud detection systems.

In terms of challenges the four themes emerged. The major challenge in using ML and AI fraud detection systems is lack of funding. Banks in Zimbabwe do not have funding to acquire these tools or to purchase licenses due to lack of external credit lines. This was echoed by P9 who stated that “Our bank would like to use these tools but we do not have money to purchase licenses to use these chatbots.” However, this is not picked up in a study by Wall (2018). This may be because Wall (2018) studies were in America, whereas this study was conducted in Zimbabwe where the economy is harsh and banks do not have extra money to adopt AI and ML systems. The other challenge is on limited AI and ML skills amongst auditing staff. This is explained by P3 who submitted that “Many auditors are not tech savvy and they cannot operate and navigate these AI and ML systems.” This different from Shinamoto (2022) studies in Japan, and this is because Japan is ahead of Zimbabwe in ICT literacy rates.

Furthermore, the study found that lack of leadership support is another challenge. Leadership support is needed when adopting ML and AI based systems because they are the policy makers, and they allocate resources. P10 said “Our leaders are hesitant to invest in AI because they think it consumes more capital.” This funding is different Russell & Norvig (2016) who viewed leadership in banks in the United Kingdom have taken a leadership role in adopting AI and ML tools. The difference may be with levels of technology, as Zimbabwe is lower than UK in terms of technology adoption rate. The final challenge established is on ethical considerations. AI and ML are viewed as unethical practices that violate the privacy of banks’ customers. This is finding is alluded to by P1 who stated that “Some of our customers will not be happy with AI and ML because it violets their privacy and secrecy.” Participants interviewed also echoed the need for regulation and this is in sync to concerns raised by Buchanan (2019), wherein she notes that uncertainties and risks in the legal and ethical realm need to be addressed before AI could fully be adopted.

5. Conclusion and Recommendations

The study concludes that privately owned banks and younger internal auditors are using AI and ML in fraud detection. The study also concludes that AI and ML are highly beneficial as they are associated with speed in identification of fraud, improved accuracy, and reduction in costs. However, the study concluded that challenges associated with AI and ML tools in fraud detection are limited skills amongst staff, limited funding, lack of leadership support and ethical considerations.

The following recommendations emanated from the study.

- Banks should adopt AI and ML as they are highly efficient in fraud detection.

- Banks should train auditing staff on the use of AI and ML in early fraud detection.

- There should be clear policies and procedures on the use of AI and ML by banks.

- Future research should focus on the use of AI in other banking activities such as handling customer complaints.

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