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Relationship between Artificial Intelligence (AI) and Fraud Detection in the Audited Financial Statement

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ABSTRACT

The relevance of AI in audit practice particularly in fraud detection had been persistently considered among auditors that were adequately familiar with the use of AI in audit investigation. This was due AI was effective in detecting fraud intelligently committed by the prepares of financial statement faster than manual test comparison. This study explored the effect of Artificial Intelligence (AI) on the detection of fraud by auditors in audited financial statements. To accomplish this objective, the researchers adopted a descriptive research design and selected a sample of 396 auditors from the Big Four audit firms. A structured questionnaire served as the data collection instrument and was distributed to the selected participants. Out of the 396 questionnaires distributed, 350 were duly completed and returned for analysis. The data were analyzed using descriptive statistics, specifically mean and standard deviation, as well as inferential statistics through the application of the Ordinary Least Squares (OLS) regression technique. The results of the analysis showed a significant positive relationship between the use of AI and the effectiveness of fraud detection. Based on the findings, the study concluded that AI improves the ability of auditors to detect fraud. It was recommended that the use of AI should be encouraged and widely adopted among auditors in Nigerian accounting firms.

Keywords: *AI, Data Mining, Fraud Detection, Expert System, Audit Practice.*

Introduction

The capacity of audit firms to carry out large investigations manually has continued to be limited due to the fact that human effort, knowledge and ability to get thing done in time are constrained by nature and human limitation. As a result of this, the need for the auditing firms in particularly the external auditors to follow the current trend in auditing practices is obvious. Globally, auditing practices have taken new form as a result of introduction of new advanced software technology in auditing. With this new technology, audit firms that are still depending on manual auditing have been pushed aside with no client to patronize them. The new advanced software in auditing practices such AI, Cloud auditing, big data, automation, data mining, machine language and image recognition used by the big four auditing firms in Nigeria have serious implication on client's patronage of new audit firms that have not adopted or switch to the use of the software in auditing. In this regard, Ojo (2025) argued that the inability of the smaller audit firm to adopt big data mining for auditing is having serious economic and market implication on the firm. The author continued by reassessing that unless the smaller audit firms switch to AI and other technology for auditing it -may be difficult for the firms to survive. The challenges of switching from manual audit to software audit or otherwise called AI does not limited to failure of the smaller audit firms to embrace the new technology, it also compasses how the audit firms may use the AI to detect fraud and carry out other qualitative audit investigation to improve shareholders confidence in the auditor work.

More so, AI helps in the detection of fraud and material misstatement intention incorporated in the prepared financial statement by the directors or preparers of the account. This capability of AI auditing to detect fraud in lager volume of financial data may take months even year for audit firm operating manually to be able to carry out. The challenge is that many auditing firm have failed to embrace the technology. This according to Aliyu (2023) may due to cost of training auditors and cost of procuring and installation associated with the AI which many smaller audit firms may not be able to procure due to financial constraint and man-power incapability.

Recent study by scholars such as Ojo (2023), Alawode (2023), Aliyu and Olorunleke (2023), and Ashiru (2024) have highlighted a notable association between artificial intelligence (AI) and auditing procedures. In contrast, studies conducted by Akinolu, Goodness, and Ogunwole (2023), Akinwale (2024), and Dele and Akinsanya (2024) were inconclusive in determining the specific effect of AI on the quality of audit reports, especially among smaller auditing firms in Nigeria. This current research seeks to bridge that gap by focusing on how AI influences audit processes within the Big Four accounting firms. Unlike earlier studies, this research utilizes primary data gathered through structured questionnaires administered to staff members of these major firms. The central goal of the study is to investigate how AI contributes to fraud detection in financial statement audits. Accordingly, the paper is structured into five major sections: an introduction, a review of relevant literature, the research methodology, findings and discussion, and a conclusion that includes actionable recommendations.

Literature Review

This review is divided into three parts, namely, conceptual, theoretical framework and empirical review of literature.

Conceptual Review

Meaning and Definition of AI

Although there is no universally accepted definition of Artificial Intelligence (AI), it is frequently understood as a technological advancement that allows machines to simulate intricate elements of human cognition (Sheikh et al., 2023), a perspective also shared by major tech corporations like Google and Microsoft (Google Cloud, n.d.; Microsoft Azure, n.d.). Nevertheless, Sheikh et al. (2023) argue that this definition is too vague, primarily because human intelligence itself lacks a precise definition, making its artificial replication difficult to conceptualize. Philosopher Daniel Dennett offers a contrasting view, asserting that AI systems should be regarded as tools rather than peers. He emphasizes that these technologies currently lack the motivations, reflective thinking, and self-directed goals necessary to critique or evolve beyond their programmed data sets (Dennett, 2019). Dennett further characterizes AI as predictive instruments—similar to oracles—that can forecast outcomes without possessing inherently human attributes such as self-awareness, moral judgment, or personality.

Sheikh et al. (2023) advocate for the adoption of a more inclusive definition put forth by the AI High-Level Expert Group (HLEC), which describes AI as “systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.” This expanded definition offers a more adaptable framework for understanding AI’s diverse functions and potential, particularly in contexts like auditing where ethical complexities are prevalent (Sheikh et al., 2023; Munoko et al., 2020; Rotolo et al., 2015). Additionally, Davenport (2018) describes AI as a collection of technologies capable of executing cognitive processes that were once exclusive to human intelligence. At its core, AI leverages foundational elements such as statistical modeling, logical rules, and semantic processing. These components can be utilized individually or in combination to create specific tools, including machine learning algorithms for predictive analysis, rule-based robotic process automation (RPA), and natural language processing systems that rely on semantic-driven computational linguistics or deep learning techniques.

AI adoption in auditing

Recent academic discussions highlight inconsistent views and limited consensus regarding the extent of Artificial Intelligence (AI) integration into auditing. Some scholars argue that the incorporation of AI in audit activities remains sluggish, mainly due to the absence of formal requirements for such technologies in prevailing auditing standards (Fotoh&Lorentzon, 2022; Issa, Sun, & Vasarhelyi, 2016). Moreover, many audit firms tend to postpone implementation due to the need for rigorous compliance protocols within the highly regulated audit sector (Cooper, Holderness, Sorensen, & Wood, 2019). In an exploratory study, Cooper et al. (2019) interviewed 14 executives responsible for Robotic Process Automation (RPA) within Big Four firms to assess its deployment in public accounting. The study revealed that RPA is more extensively applied in tax and advisory services than in audit functions, primarily because of the increased regulatory oversight that audits of public companies attract. Nevertheless, the researchers also noted that the globally uniform audit frameworks make the auditing process well-suited for scaling RPA technologies, unlike tax services, which often require country-specific customization. Although adoption has been cautious, firms were reportedly taking active steps to embed RPA into audit testing processes, viewing it as an entry point for broader AI adoption in the accounting profession.

Despite the strategic fit of RPA for audit work, research by Eulerich, Pawlowski, Waddoups, and Wood (2022) found persistent slow adoption rates and a high incidence of implementation failures. To assist auditors in identifying suitable processes for automation, they proposed a structured three-phase model for RPA integration. Supporting earlier findings, Fedyk et al. (2022) conducted interviews with 17 senior audit professionals and technology executives from eight top-tier firms. Their study confirmed that RPA is mostly used for internal support tasks and noted a recent decline in its deployment. Likewise, Bakarich and O'Brien (2021) observed that RPA and machine learning applications are still not widespread among auditors or their clients, although future adoption is expected to grow. Samiolo et al. (2023) found that while data analytics tools are commonly implemented, AI usage remains minimal and typically limited to basic machine learning trials. In a collaborative workshop involving academic experts and auditors, Boritz and Stratopoulos (2023) referenced a computer science professor who pointed out that the so-called AI applications discussed were not truly intelligent systems but rather sophisticated data management techniques.

In contrast to current adoption patterns, Issa et al. (2016) had earlier forecasted that technologies such as optical character recognition, cloud-based solutions, electronic documentation, and smart contracts would significantly alter the landscape of audit practices. They called for further research into how AI might redefine traditional auditing methods. Expanding on this, Kokina and Davenport (2017) introduced a framework that classifies emerging technologies based on the tasks they support and the complexity of their intelligence. Their analysis indicated that innovation within auditing has been largely concentrated on operational tasks, including compiling client request lists, document examination, managing confirmations, inventory verifications, researching disclosure requirements, and performing risk assessments using predictive models.

More contemporary evidence from Fedyk et al. (2022) highlights a growing trend in both large and mid-tier audit firms toward greater technological integration, with AI positioned as a transformative tool for boosting audit efficiency and quality. Their research reveals that AI is actively used to detect irregularities, flag possible fraudulent activities through machine learning algorithms, align transactional data such as orders and payments, extract and analyze contracts using OCR technology, and perform benchmarking using publicly sourced datasets. These applications not only enhance audit reliability but have also contributed to reduced audit costs. Additionally, Seethamraju and Hecimovic (2022) outline a range of benefits attributed to AI, including the identification of anomalous transactions for testing, conducting audits across complete datasets, automating confirmations, implementing three-way data matching and reconciliations, executing detailed analytical procedures, and managing client audit queries. While many of these processes were once handled by conventional rule-based systems, the enhanced capabilities of modern AI now enable deeper, data-centric, and forward-looking decision-making within auditing workflows.

Challenges to AI adoption in auditing

Kokina and Davenport (2017) pinpoint a major barrier to the adoption of Artificial Intelligence (AI) in auditing: the lack of uniformity in data formats across clients. This concern is echoed by Almufadda and Almezeini (2022), whose review of existing literature outlines a variety of AI tools employed by prominent accounting firms. They highlight several key challenges namely, insufficient data quality, missing or incomplete datasets, algorithmic bias, and underdeveloped AI infrastructure, as significant risks associated with AI integration. To better understand and address these risks, they recommend further exploratory studies, particularly those that use interviews to gather qualitative insights.

In a similar vein, Seethamraju and Hecimovic (2022) identify additional obstacles tied to technological readiness. These include the immature state of many AI solutions, the prevalence of low-quality client data, and the general lack of confidence in these emerging systems. They further note that many third-party AI tools are incompatible with existing audit technologies and client ERP systems, primarily because data cleansing is resource-intensive and because AI systems often require customization to meet the specific demands of different industries. Moreover, since many

AI applications are still evolving, the tools may not yet be robust enough for seamless implementation. From the client side, concerns such as poor data integration and hidden biases in algorithms also pose major challenges.

At the institutional level, a clear disparity exists between larger and smaller audit firms regarding resource capacity. While the Big Four firms have invested heavily in global AI initiatives and workforce upskilling, smaller audit firms often depend on generic commercial AI platforms and typically lack in-house IT specialists trained to interpret AI-generated results. These limitations are compounded by the financial burden and logistical complexity of providing adequate training for existing staff.

Human-related challenges also significantly influence AI adoption. Fedyk et al. (2022) note that a shortage of skilled professionals is the single most pressing issue hindering the successful implementation of AI in audit processes. In addition to the need for technical competencies, auditors' skepticism toward AI-generated insights further complicates adoption. This skepticism largely stems from a lack of transparency in how AI outputs are generated and the auditors' limited involvement in the development and design of these tools. As a result, many professionals are reluctant to place full trust in AI-assisted decision-making (Seethamraju&Hecimovic, 2022; Samiolo et al., 2023).

Only a limited number of studies have explored the ethical dimensions of AI in the auditing and accounting space. Munoko et al. (2020), drawing on ethical theories and bibliometric methods, investigate a wide range of ethical concerns tied to AI-enabled auditing. These include issues such as lack of transparency, data privacy threats, equitable data use, and the need for user responsibility and accountability. They also raise important questions about how AI may impact audit quality, professional judgment, and the degree of skepticism expected in the profession, while stressing the need for strong governance and competent oversight of AI systems. Building on this, Lehner et al. (2022) conducted a theory-driven literature review and outlined five core ethical challenges in AI-based accounting: ensuring objectivity, protecting privacy and data, maintaining transparency, enforcing accountability, and fostering trust. Their work underscores the importance of cultivating a responsible and informed approach to AI use, while acknowledging the technology's inherent limitations.

Types of AI

Ojo (2023) argued that there are different types of AI but the most common are;

Data mining

Data mining is the analytical process of exploring large datasets to uncover significant patterns and correlations that aid in business decision-making and problem resolution, as highlighted by Ayokunle (2023). Over the last ten years, various researchers have introduced conceptual models emphasizing the benefits of combining data mining with continuous auditing. However, the transition from theory to practice has encountered several operational hurdles (Ojo, 2023). Dagunduro et al. (2023) note that expert system software can be engineered to tackle problems involving multiple alternatives, especially when such problems follow a logical sequence of reasoning. Consequently, fields that depend heavily on expert knowledge or specialized judgment stand to gain considerably from expert system applications. The rising interest in data mining within the auditing sector is largely attributed to the growing intricacy of financial transactions and the increased potential for data manipulation enabled by modern digital platforms. James asserts that data mining has become an indispensable tool in auditing, enhancing auditors' ability to efficiently manage and interpret extensive datasets during the financial statement assurance process.

Machine learning

Machine learning, a specialized area within computer science, centers on the creation of algorithms that employ statistical methods to identify trends and associations within extensive datasets. The primary objective is to enable accurate forecasting of future occurrences. This technology has found widespread application in fields such as finance, healthcare, biology, and education. Although definitions may vary slightly among researchers, there is general agreement that machine learning empowers computers to draw insights from historical data and utilize those insights to predict future events. According to Ojo (2023), the process involves constructing mathematical models using sample data and testing their predictive effectiveness on new, previously unseen inputs. Its utility spans numerous real-world scenarios, particularly in analyzing data to infer likely outcomes under similar conditions.

When integrated with other advanced technologies like big data analytics and blockchain, machine learning is expected to drive significant changes in both accounting and auditing practices. These combined innovations are set to improve automation and enable more effective examination of large, complex financial datasets. In the auditing domain, leading accounting firms have already adopted machine learning tools to automate labor-intensive procedures, identify unusual transactions or discrepancies, and highlight financial activities that fall outside of established patterns.

Image recognition

Image recognition involves the identification and classification of elements within a digital image. Also referred to as photo or picture recognition, this method seeks to categorize detected objects into predefined groups, an enduring challenge within the field of computer vision (see sources [35, 22, 36]). Owing to this function, the term "object recognition" is frequently used interchangeably with image recognition. On the other hand, image detection refers to the process of identifying several objects within a single image, with an emphasis on distinguishing among various entities and determining how many unique objects are present (sources [37, 38]). In more technologically advanced countries, image detection has been widely adopted for tasks such as auditing financial records and uncovering fraudulent practices. However, in developing regions—including Nigeria, Ghana, and many other African nations—the use of such advanced technologies in accounting and auditing remains relatively underdeveloped and limited in scope.

Expert Systems

Artificial intelligence applications known as "expert systems" emerged in the 1980s and have since evolved to a level of sophistication that enables them to perform tasks traditionally carried out by human specialists in specific decision-making contexts. These systems are among the most widely used forms of artificial intelligence, primarily due to their user-friendly nature. As described by James (2014), expert systems are software programs designed to replicate the reasoning processes of professionals within a particular domain. They are commonly developed using expert system shells, which are specialized software development environments that facilitate the creation of expert or knowledge-based systems. The foundational premise of expert systems is that they can be designed to address problems that involve choosing from a predefined set of alternatives using logical rules. As such, expert systems are applicable in any field where expert knowledge is needed to guide decision-making and can be of value to individuals or organizations lacking such expertise (Taghizadeh et al., 2018).

Intelligent Agents

An intelligent agent is defined as a software application that performs a series of tasks on behalf of a user or another program, exhibiting a certain level of independence or autonomy, while utilizing embedded knowledge or representations of the user’s intentions and objectives (Eno et al., 2019). In response to the growing challenge of information overload brought about by increasingly interconnected business environments, intelligent agent technology is recognized as one of the most promising solutions. Typically, users interact with these systems by completing a standardized information profile or by using a graphical user interface (GUI) to specify their goals. This user input is then received and processed by the intelligent agent system.

Once activated, the intelligent agent transmits the relevant data across the internet or another established network infrastructure. It can independently navigate through online platforms and network environments to access supplier hubs, digital storefronts, and directory services as needed. Ultimately, the intelligent agent reaches the source databases or other data repositories that store the requested financial information. It then performs the required search or transaction and returns results to the user. Through this process, the agent demonstrates autonomy, decision-making ability, and reasoning capabilities, thereby validating its role as an intelligent system (Shaher, 2020).

Efficacy of audit practice

Auditing entails an impartial examination of an organization’s financial documentation, which commonly includes essential statements such as the income statement, balance sheet, cash flow statement, statement of changes in equity, and the related notes that explain the accounting methods applied (Ojo, 2023). The fundamental aim of this process is to provide an independent assessment of whether the financial reports accurately reflect the organization’s financial status as of the reporting date. As corporate operations become more multifaceted, the adoption of technology-driven decision-support tools has become increasingly important in enhancing audit effectiveness. Artificial Intelligence (AI), in particular, is revolutionizing the auditing landscape by automating numerous tasks that were once manually executed, such as data entry (Ashiru, 2024).

Unlike human auditors, AI systems are capable of evaluating entire datasets swiftly, designing audit procedures, and generating preliminary audit reports with a higher degree of accuracy. These systems can also reduce error rates by automating data capture, detecting irregular transactions, and limiting human involvement in repetitive tasks (Olorunleke, 2023). Understanding how AI adds value to the auditing process requires a clear grasp of how audits are conducted. An audit involves collecting and analyzing evidence to draw conclusions about the reliability of a company's financial statements. Since audit approaches are customized based on each client's internal controls and risk levels, no two audits follow an identical path. Nonetheless, AI tools can enhance precision and productivity throughout all audit stages, serving as an integrative tool that ensures a continuous flow of information from one phase to the next. The key phases of the audit cycle typically include initial client engagement, audit planning, understanding the client's operations, identifying and assessing risks, gathering and recording evidence, finalizing audit procedures, and issuing the audit opinion.

AI in auditing and its implications

Historically,the auditing field has demonstrated a cautious approach toward adopting new technologies (Rotolo et al., 2015). This reluctance stems from its dependence on manual, labor-intensive processes, the intricacy of professional judgment involved, and the strict regulatory frameworks that govern auditing practices (Issa et al., 2016). Furthermore, the need for auditors to exercise a high level of professional skepticism and discretion presents additional barriers to the seamless integration of advanced technologies (IESBA, 2023). According to Fotoh and Lorentzon (2023), the absence of explicit regulatory directives further discourages auditors from embracing digital tools and platforms. Nevertheless, Cooper et al. (2019) observe a notable shift among the Big Four auditing firms toward adopting technology-enhanced audit procedures—an evolution that holds the potential to transform the auditing profession fundamentally.

Ojo (2023) identifies several significant functions that Artificial Intelligence (AI) is beginning to perform within auditing. These include the streamlining of repetitive tasks, more comprehensive data analysis, enhanced identification of unusual patterns, and improved risk evaluation mechanisms. The incorporation of AI also contributes to the production of higher-quality audit outcomes, thereby reinforcing its increasing importance and acceptance in the auditing field.

Challenges and Synergies with AI usage in the auditing process

The hesitation and cautious attitude many auditors exhibit toward the adoption of algorithmic systems and artificial intelligence (AI) is not entirely unwarranted (Commerford et al., 2021). Research by Arnold et al. (2004) revealed that the use of intelligent decision-support systems—precursors to today's AI tools—can adversely affect the judgment of less experienced auditors. This outcome is consistent with the Theory of Technology Dominance, which suggests that sophisticated technologies yield the best results when operated by users with substantial knowledge and experience (Arnold & Sutton, 1998). Their findings indicated that novice auditors using the decision aid were prone to cognitive bias, particularly in giving undue emphasis to the most recent information available. Repeated reliance on the tool only amplified this bias over time. In contrast, seasoned auditors utilizing the same system demonstrated more accurate judgment and were less influenced by such biases.

Brynjolfsson and McAfee (2014) offer a compelling illustration through a chess tournament example, where a team made up of a human and a computer program outperformed both expert human players and standalone chess engines. This case supports the idea that combining human insight with machine accuracy can produce superior outcomes. Echoing this view, Sutton et al. (2016) predict that such collaborative approaches will be increasingly vital as AI technologies become more embedded in accounting and auditing practices. Lehner et al. (2022) also advocate for this partnership, emphasizing that collaboration between humans and AI not only enhances transparency but also helps create systems that are auditable, traceable, and ethically accountable.

AI in the Big Four

The world's top-tier accounting firms—Deloitte, PricewaterhouseCoopers (PwC), Ernst & Young (EY), and KPMG—commonly referred to as the Big Four, have taken significant steps to incorporate Artificial Intelligence (AI) into their auditing and consulting operations to improve both quality and efficiency.

Deloitte, for instance, has implemented a variety of AI-powered tools designed to support and refine its audit processes. Among them is the Guided Risk Assessment Personal Assistant (GRAPA), which aids auditors in crafting risk assessments by blending their own professional judgment with insights drawn from peer collaboration (Deloitte, 2018). The firm has also introduced intelligent chatbot technologies to assist auditors in interpreting intricate regulatory and legal requirements, as well as accounting and auditing standards (Deloitte, 2018). A 2024 Financial Times report highlights that Deloitte recently launched a generative AI assistant accessible to 75,000 employees across Europe and the Middle East. This tool is intended to boost workplace productivity by supporting users in tasks like drafting emails, generating presentations, and writing code. Access is granted only after mandatory training is completed (Financial Times, 2024).

PwC has taken similar strides by establishing an AI-focused audit innovation lab to elevate audit quality, streamline operations, automate routine functions, and enhance data analysis processes (Zhang et al., 2020). One of the firm's hallmark AI applications is GL.ai, a machine learning system built upon PwC's global expertise and data knowledge base (PwC, 2018; Zhang et al., 2020). This tool is capable of spotting anomalies in financial data by applying advanced analytics coupled with domain knowledge. PwC has also developed automated reporting systems for anti-bribery and anti-corruption efforts—areas that require complex risk-based assessments of vast data volumes (Zhang et al., 2020). According to The Wall Street Journal (2023), PwC has committed $1 billion toward AI initiatives in the United States over three years, in partnership with Microsoft and OpenAI. This investment aims to integrate AI into various firm functions, including tax, audit, and advisory services, and features comprehensive staff training in AI utilization.

Ernst & Young (EY) has similarly incorporated several AI technologies—such as Robotic Process Automation (RPA), Natural Language Processing (NLP), and drones—into its digital transformation agenda (Zhang et al., 2020). The firm has allocated $1 billion to develop an advanced Assurance technology platform designed to increase transparency, strengthen trust, and transform audit practices (EY, 2022). According to EY's global assurance digital leader, Marc Jeschonneck, this investment not only enhances audit quality but also improves engagement for auditors and their clients. EY's digital audit framework revolves around three pillars: (1) promoting seamless collaboration between auditors and clients through the EY Canvas cloud platform; (2) automating audit tasks via EY Smart Automation, which integrates AI and machine learning; and (3) using data analytics to generate reliable audit evidence and add value at each stage of the audit process. Central to this approach is EY Helix, a specialized data analysis tool that allows auditors to examine extensive datasets, identify emerging risks, and extract meaningful insights. Machine learning models are also employed to detect fraud and boost audit team performance (Zhang et al., 2020).

KPMG has also made substantial progress in integrating Artificial Intelligence (AI) into its audit operations through the launch of its proprietary AI platform, KPMG Ignite. This platform incorporates a range of advanced technologies—including machine learning, deep learning, natural language processing, and image recognition—to facilitate automated analysis and review of documents (KPMG, 2024). KPMG Ignite is engineered to expedite the design and deployment of AI-driven solutions across multiple stages of the audit process (Zhang et al., 2020). According to Sebastian Stöckle, the firm's global leader for audit innovation, AI adoption significantly boosts the firm's ability to detect potentially high-risk financial transactions. He further explains that automating routine and labor-intensive procedures enables auditors to focus more on strategic and high-value aspects of their work. In addition to improving efficiency, the Ignite platform enhances the objectivity and accuracy of data interpretation and estimation. KPMG has also implemented a forward-thinking approach to evaluating risk, known as Dynamic Risk Assessment. This technique applies principles from actuarial science, advanced algorithms, mathematical models, and robust data analytics to assess risk through four key lenses: potential impact, probability of occurrence, interdependence with other risks, and the speed at which the risk may materialize (Zhang et al., 2020).

Relationship between AI and Fraud Detection

As the field of auditing continues to evolve, the integration of Artificial Intelligence (AI) is significantly reshaping how data is analyzed and how anomalies are detected (Peng et al., 2023). This section explores how AI improves auditors' analytical capabilities, particularly in identifying unusual activities and potential fraud. It also presents real-world examples that illustrate how AI-based systems enhance data evaluation and anomaly identification, thereby promoting more precise and efficient audit outcomes. Since data analysis is fundamental to auditing, AI introduces advanced techniques that surpass conventional audit tools. By leveraging sophisticated algorithms and computational power, AI enables auditors to process large volumes of financial data efficiently, uncover hidden trends, and derive actionable insights.

Through algorithms designed for pattern detection, AI helps auditors discover complex interrelationships within datasets—connections that traditional analysis might miss. This deeper understanding of transactional behavior and operational dynamics equips auditors with better tools to evaluate financial risks. In addition, AI supports predictive analytics, which empowers auditors to anticipate potential risks and future trends. Such foresight allows for proactive risk management and offers businesses valuable strategic recommendations. AI systems also incorporate Natural Language Processing (NLP), allowing auditors to interpret unstructured text-based information, such as financial disclosures, contracts, and internal communications (Faccia&Petratos, 2022). This capability expands the scope of audit analysis by extracting meaningful insights from textual sources that would otherwise remain unexamined. Furthermore, AI enhances the clarity and accessibility of audit results through dynamic data visualizations, converting complex data into easily interpretable visual formats for more effective communication with stakeholders.

Anomaly detection is a critical aspect of audit work, and AI significantly strengthens auditors' ability to detect discrepancies, errors, and fraudulent behavior. By training machine learning models on historical financial data, AI systems can establish baselines of normal activity and flag deviations from expected patterns as potential red flags. This predictive, data-centric approach enables a more vigilant and timely identification of audit risks. AI also supports real-time monitoring of business transactions and financial records, allowing for the early identification of unusual trends or behaviors that may require investigation (Patel, 2023). By analyzing behavioral patterns in user and transactional data, AI systems can uncover anomalies that diverge from established norms, helping auditors detect irregularities that may otherwise go unnoticed.

Historical financial scandals provide compelling evidence of how AI could have improved detection mechanisms. For example, in the case of Enron—a company whose collapse was caused by complex and concealed financial misconduct—AI's data-driven anomaly detection tools might have identified suspicious patterns in financial reporting early on, potentially averting the eventual fallout. Similarly, during the Wells Fargo scandal, where employees created unauthorized customer accounts to meet sales targets, AI technologies could have flagged the unusual surge in account openings. By recognizing these deviations from standard business behavior, AI could have triggered alerts prompting earlier internal reviews, potentially uncovering unethical practices before they escalated (Brintrup et al., 2023).

When applied to blockchain environments, Artificial Intelligence (AI) significantly enhances data evaluation by analyzing the intricacies of decentralized transaction structures. Using sophisticated anomaly detection algorithms, AI can uncover inconsistencies or deviations within blockchain entries, offering auditors a powerful tool to uphold the accuracy and transparency of financial data. This application of AI is not limited to auditing blockchain systems alone; it has also proven highly effective in detecting fraudulent financial behavior. For instance, AI—particularly through machine learning models—has been instrumental in identifying credit card fraud by analyzing transactional trends, user behavior, and contextual data to pinpoint suspicious patterns (Shi et al., 2020). This functionality is crucial for reducing financial risk and preventing economic losses for both consumers and organizations.

More broadly, the global integration of AI into auditing practices signifies a paradigm shift toward more advanced and resilient auditing methodologies. AI's ability to process massive datasets, detect subtle anomalies, and conduct continuous real-time analysis elevates the audit function from a reactive exercise to a proactive safeguard. Practical evidence from various sectors highlights the effectiveness of AI in uncovering inconsistencies and preventing fraud, underscoring its value in enhancing both the credibility and efficiency of audits (Kunduru, 2023).As AI becomes more embedded in audit workflows, the profession moves closer to realizing a future marked by heightened transparency, stronger oversight, and more insightful financial reporting.

Theoretical Framework

This research is anchored in Agency Theory, originally introduced by Jensen and Meckling (1976), which continues to serve as a cornerstone in the field of auditing. The theory articulates the relationship between principals (investors) and agents (managers), where the latter are entrusted to act in the best interests of the former. In an ideal setting, agents align their actions with the goals of the principals. However, in practice, managers may prioritize personal interests that diverge from those of the investors. This potential misalignment underscores the importance of auditing as a mechanism to ensure managerial accountability and integrity (Commerford et al., 2019). Within this framework, auditors act as independent monitors who provide investors with credible evaluations of management's financial disclosures, enabling informed decisions about investment activities—whether to acquire, retain, or divest (Shogren et al., 2017).

As corporate entities grow in scale and complexity, the volume of financial data expands, thereby increasing the need for precise and timely audits. Auditors are expected to maintain high levels of accuracy and dependability in their assessments of financial information (Blair & Stout, 2017). In this regard, Artificial Intelligence (AI) is emerging as a valuable tool for fulfilling the objectives outlined by Agency Theory. AI enhances audit capabilities by enabling remote access to financial data and facilitating real-time analysis across dispersed geographic locations—a concept referred to as "remoteness" (Blair & Stout, 2017). This function allows auditors to bridge the physical gap between data sources and decision-makers, thus improving oversight effectiveness.

Additionally, AI plays a pivotal role in simplifying the evaluation of complex financial records. As the intricacy of financial reporting increases, stakeholders often struggle to verify the authenticity and reliability of such reports. By automating data analysis and applying consistent logic to financial reviews, AI contributes to the accuracy and credibility of financial statements. In doing so, it supports Agency Theory by helping reduce information asymmetry and potential self-serving behavior by management. Since financial reporting may be influenced by directors seeking to highlight favorable outcomes, the objectivity offered by AI helps curb biased representations and enhances investor trust (Blair et al., 2017).

Guided by this theoretical foundation, the present study is designed to evaluate the following hypothesis:

H_O: There is no significant effect of AI on the quality of the audited report.

Empirical Review

Monal et al. (2022) examined how Artificial Intelligence (AI) is influencing the evolution of the accounting and auditing professions. Drawing on secondary sources, their study focused on 359 accounting firms based in Bahrain. The researchers employed a quantitative content analysis approach, using manual coding derived from inductively developed categories. Their results highlighted that the integration of AI holds promise for fostering a more innovative and dynamic professional environment, potentially enhancing creativity and stimulating growth within both fields.

In a related study, Awotomilusi et al. (2022) explored the effects of adopting cloud computing on the efficiency of accounting operations in Nigeria. The research methodology involved administering structured questionnaires to employees of deposit money banks. Collected data were analyzed using frequency distribution and ordinary least squares regression techniques. Findings revealed a statistically significant and positive correlation between cloud computing adoption and improved accounting performance. Additionally, the study showed that variables like technological advancement and enhanced security were positively associated with accounting efficiency, while cost-effectiveness had a negative impact on operational effectiveness.

Hassan (2022) conducted a semi-systematic narrative review to explore how AI is reshaping the accounting and auditing landscape. The review emphasized that accounting professionals must adapt in response to the disruptive potential of emerging technologies. The author underscored the importance of interdisciplinary collaboration and further research to facilitate effective AI integration. The study concluded that AI implementation could significantly enhance productivity, accuracy, and operational efficiency within the profession.

In a broader analysis, Onwughai (2022) investigated how AI and machine learning are transforming accounting functions within business organizations. This mixed-methods study utilized both survey questionnaires and a qualitative literature review to gather insights from prior research and industry reports. The findings indicated that AI is likely to automate routine, repetitive accounting processes. However, this shift also presents an opportunity for professionals to move into more strategic and value-oriented roles, thereby increasing their relevance in a technology-driven environment.

Finally, Akinadewo (2021) examined the relationship between AI adoption and accountants' approach to performing accounting functions. The study utilized a structured questionnaire and targeted a sample of 205 accountants with experience in systems applications for financial transactions. Using a purposive sampling technique, the study revealed that AI has a significant positive effect on how accountants' approach and execute their professional responsibilities.

Methodology

This study focused on the Big Four audit firms operating in Lagos State, Nigeria. A descriptive research design was employed to thoroughly investigate how Artificial Intelligence (AI) influences fraud detection, risk evaluation, and the quality of audit reports. The study population was estimated at around 45,000 individuals, encompassing full-time staff, partners, and associate auditors affiliated with these firms across the country. Interns and part-time workers were deliberately excluded to maintain a focus on professionals with substantial audit responsibilities.

To ensure the selection of appropriately qualified respondents, the study adopted a purposive sampling strategy. Participants were chosen based on specific inclusion criteria: demonstrable AI compliance, at least five years of experience working with AI-related audit systems, familiarity with AI-generated audit reports, and competence in applying AI tools for fraud detection and risk assessment. Eligibility was limited to senior associates, partners, or their designated representatives. The sample size was calculated using Yamane's (1967) formula, applying a 5% margin of error, which yielded a minimum required sample of 396 qualified auditors. Selection continued until this target was met.

Primary data were obtained using a structured questionnaire, which was distributed via the official email addresses of the audit firms after securing the necessary institutional clearances. The questionnaire's content validity was established through expert evaluation by professionals with expertise in both AI technologies and audit practices. Feedback from these experts led to several revisions, ensuring the instrument's clarity, relevance, and technical accuracy.

To verify the reliability of the instrument, a pilot study was conducted with 30 auditors based in Akure and Ado-Ekiti. The Cronbach's Alpha test results indicated strong internal consistency: AI and audit quality (0.89), AI and fraud detection (0.87), AI and risk evaluation (0.90), and general AI application (0.94). Data analysis involved the use of descriptive statistics, particularly means and standard deviations, to summarize the responses. Inferential analysis was conducted using Ordinary Least Squares (OLS) regression to test the hypothesis and address the research objectives. This analytical method was deemed suitable given the early stage of AI adoption in Nigeria's audit industry and the limited availability of dependable secondary data.

Result and Discussion

Table 1 Frequency Distribution of Respondent Demographic Characteristics

Table 1 presented the frequency distribution of respondent demographic characteristics.

Demographic Variable	***Frequency***	***% Percentage***
Age in years		
Less than 30	50	14.29
30-39	120	34.28
40-49	80	22.86
50-59	60	17.14
60 and above	40	11.43
Status in the Organization		
Senior Partner	40	11.43
Associate Partner	60	17.14
Senior Auditors	100	28.57
Auditors	130	37.14
Other	20	5.71
Responsibility		
Forensic Audit with AI	42	12.00
Forensic Accounting with AI	20	5.71

General Audit with AI	180	51.43
Software Audit (AI, Large Data, Data mining etc.)	88	25.14
Other	20	5.71
Highest Educational Qualification		
OND/NCE	12	3.43
HND/B.Sc.	220	62.86
PGD/MSC/MBA	50	14.29
Other	68	19.43
Professional Qualification		
ICAN	280	80.00
ANAN	40	11.43
Other	30	8.57

Source: Researcher's Fieldwork, 2025

Table 1 presents the frequency distribution of the demographic characteristics of respondents in the study. The majority of respondents (34.28%) were between the ages of 30–39, followed by those aged 40–49 (22.86%), while only 11.43% were 60 years and above. Regarding organizational status, auditors comprised the largest group (37.14%), followed by senior auditors (28.57%), while senior and associate partners made up 11.43% and 17.14% respectively. In terms of responsibilities, over half (51.43%) were involved in general audit using AI, with 25.14% engaged in software audit involving AI, large data, and data mining. Educational qualifications showed that most respondents held HND/B.Sc. degrees (62.86%), while only 3.43% had OND/NCE. Additionally, 14.29% had postgraduate degrees (PGD/M.Sc./MBA). Regarding professional qualifications, a vast majority (80%) were ICAN-certified, followed by 11.43% with ANAN certification, and 8.57% holding other qualifications. This demographic distribution reflects a well-diversified and professionally qualified respondent pool.

Table 2 Mean and Standard Deviation Computed for the variable of AI

S/N	Variable	N	Mean	STD	Rank	Remark
1	Expert system has enhanced the adoption of AI in audit practice.	350	4.34	0.23	2nd	Determinant of AI in audit Practice
2	Machine learning inbuilt in AI audit software has helped in handling large volume of financial data in order to make prediction for unknow future event.	350	4.63	0.11	1st	Determinant of AI in audit Practice
3	Intelligent agents inbuilt in AI software audit helps auditors to performs a set of operations on behalf of a user/another programme with some degree of independence or autonomy.	350	3.78	0.72	4th	Determinant of AI in audit Practice
4	The integration of data mining in AI audit software has improved audit evidence.	350	4.12	0.31	3rd	Determinant of AI in audit Practice

Source: Researcher's Fieldwork, 2025 **Acceptable mean = 3.00 ** and ** Rank was carried out on the basis of STD

Table 2 presents the respondents' perception of the determinants of Artificial Intelligence (AI) adoption in audit practice, using the mean and standard deviation as statistical tools. All variables recorded mean scores above the acceptable threshold of 3.00, confirming them as valid determinants. The ranking of the variables was based on their standard deviation, with lower values indicating greater consensus among the respondents.The statement *"Machine learning inbuilt in AI audit software has helped in handling large volumes of financial data in order to make prediction for unknown future events"* recorded the highest mean value (M = 4.63, SD = 0.11), indicating a strong level of agreement among respondents. This suggests that machine learning is the most influential driver of AI adoption in audit practice. Machine learning enables auditors to process large datasets efficiently, identify patterns, and forecast risks or errors. This finding aligns with Adebayo (2023), who emphasized that machine learning significantly enhances predictive analytics capabilities in auditing, allowing for the detection of irregularities and subtle trends that might escape manual scrutiny. As a result, auditors are better equipped to make data-informed decisions in real time.

Following closely was the item "*Expert system has enhanced the adoption of AI in audit practice*" (M = 4.34, SD = 0.23). Expert systems, which replicate the decision-making process of human auditors using programmed logic and rule-based reasoning, were highly rated for their contribution to audit quality. The positive perception of respondents suggests confidence in expert systems as tools for improving consistency and reducing cognitive bias in complex audit scenarios. This perspective is supported by Ibrahim and Yusuf (2022), who argued that expert systems minimize human errors and facilitate more standardized audit judgments, ultimately enhancing the efficiency and reliability of audit outcomes.

The third item, "*The integration of data mining in AI audit software has improved audit evidence*," also received strong support (M = 4.12, SD = 0.31), indicating that respondents value the role of data mining in extracting meaningful information from voluminous and diverse datasets. Data mining enables auditors to identify irregularities, fraud risks, and patterns that would otherwise remain undetected. In line with this view, Okonkwo (2023) reported that AI-powered data mining tools provide auditors with deep insights into transactional data, thus contributing to more comprehensive and credible audit evidence, particularly in data-intensive environments.

Lastly, the item "*Intelligent agents inbuilt in AI software audit helps auditors to perform a set of operations on behalf of a user/another program with some degree of independence or autonomy*" had the lowest mean score (M = 3.78, SD = 0.72), although it remained above the acceptable benchmark. This suggests a moderate level of recognition of intelligent agents' utility, possibly reflecting limited familiarity or practical exposure among auditors. Intelligent agents can autonomously execute audit tasks, flag anomalies, and provide continuous system monitoring. Oyeleke (2023) affirmed that such agents enhance operational efficiency by automating repetitive processes and offering real-time oversight. Despite the lower consensus, their acknowledgment as a determinant highlights the evolving understanding of AI's autonomous functions within audit practices.

Table 3 Mean and standard deviation computed for the respondent perception on the relationship between AI and Fraud Detection

S/N	Variable	N	Mean	STD	Rank	Remark
1	The activities of unscrupulous preparers of the financial statement may be exposed by AI audit practice.	350	4.34	0.27	4th	Contributed to Fraud detection
2	The willful omission and commission committed by the preparers of financial statement cannot be hidden from audit investigation through AI.	350	4.78	0.10	1st	Contributed to Fraud detection
3	Corporate frauds involve the director and manager of an organization are exposed by adoption of AI in audit practice.	350	4.33	0.20	3rd	Contributed to Fraud detection
4	The matching-order verification integrated in the AI audit software has made it impossible for incidence of material misstatement not be flagged by AI use in Audit practice.	350	4.56	0.15	2nd	Contributed to Fraud detection

5	The independence and objectivity of the auditor have been protected due to capacity of AI to detect fraudulent activities committed by the management in the prepared financial statement.	350	4.21	0.31	5th	Contributed to Fraud detection

Source: Researcher's Fieldwork, 2025 **Acceptable mean = 3.00 ** and ** Rank was carried out on the basis of STD

Table 3 presents respondents' assessments of how Artificial Intelligence (AI) influences fraud detection in audit practices. All items recorded mean scores well above the acceptable benchmark of 3.00, indicating a strong consensus that AI significantly contributes to identifying fraudulent behaviors within financial reporting processes.

A high level of agreement was observed regarding the statement, "The activities of unscrupulous preparers of the financial statement may be exposed by AI audit practice" (M = 4.34, SD = 0.27). This implies that AI systems equipped with adaptive interfaces and automated verification tools can effectively trace and cross-check transactions against original records to uncover intentional falsifications. This aligns with the findings of Ashiru (2023) who emphasized that AI enhances transparency by enabling full-data audits and anomaly detection, thus reducing the risk of human oversight or manipulation.

The item with the highest level of agreement was, "The willful omission and commission committed by the preparers of financial statements cannot be hidden from audit investigation through AI" (M = 4.78, SD = 0.10). This underscores the capability of AI to reprocess and validate transactions in real time, enhancing the accuracy and completeness of audit trails. Ojo (2023) highlights that AI audit tools are capable of detecting even subtle omissions through automated tracking of inconsistencies, making them essential for fraud detection.

Respondents also strongly agreed with the claim that "corporate frauds involving the director and manager of an organization are exposed by adoption of AI in audit practice" (M = 4.33, SD = 0.20). This finding reflects the view that AI can identify top-level manipulation of financial data. In line with this, Bello (2023) observed that intelligent AI systems are increasingly being deployed in Nigerian audit firms to expose executive-level fraud schemes, especially those involving override of controls.

Another item that received a high level of agreement was "the matching-order verification integrated in the AI audit software has made it impossible for incidence of material misstatement not be flagged by AI use in audit practice" (M = 4.56, SD = 0.15). This result reinforces the understanding that AI systems enable continuous monitoring and instant matching of financial data against original entries. Evidence from Eze and Ayeni (2022) affirms that AI-enabled matching-order techniques significantly enhance auditors' ability to detect material misstatements promptly.

Lastly, the statement "the independence and objectivity of the auditor have been protected due to the capacity of AI to detect fraudulent activities committed by the management in the prepared financial statement" also received broad agreement (M = 4.21, SD = 0.31). This implies that AI serves as a buffer between auditors and undue management influence by independently verifying data integrity. Udo and Kehinde (2024) emphasized that AI's analytical objectivity strengthens auditors' confidence to report anomalies without bias, thereby preserving ethical standards. Although this item ranked fifth, it still demonstrated a notable contribution to enhancing audit integrity through AI adoption.

Test of Hypothesis

Objective: Evaluate the relationship between AI and fraud detection in the audited financial statement.

H_O: There is no significant effect of AI on the quality of the audited report.

Table 4 Regression Result

Dependent Variable: Fraud Detection (FD)

Variable	Coefficient	Standard Error	T-calculated	P-value
C	-83.62904	498.6295	-0.167718	0.8683
AI	0.423651	0.167350	2.531529	0.0186
	OTHER	**TEST**	**STATISTICS**	

R-squared	0.792168		Mean dependent var	205.444
Adjusted R-squared	0.786719		S.D. dependent var 2696.018	696.018
S.E. of regression	310.6963		Akaike info criterion	14.61212
Sum squared resid	2220241.		Schwarz criterion	15.32990
Log likelihood	-275.2425		Hannan-Quinn criter.	14.87165
F-statistic	182.0971		Durbin-Watson stat	1.789666
Prob(F-statistic)	0.000000			

Source: Researcher's Computation, 2025 ** 5% significant Level was chosen for the test

The Ordinary Least Squares (OLS) regression analysis in table 4 reveals a strong and statistically significant influence of Artificial Intelligence (AI) on fraud detection, which serves as a proxy for the quality of the audited financial report. The model explains approximately 79.2 percent of the variation in fraud detection, as indicated by an R-squared value of 0.792, demonstrating AI's critical role in enhancing auditors' ability to identify fraudulent activities within financial statements.The coefficient of 0.4237 implies that for every unit increase in AI application, there is a corresponding 42.37 percent improvement in fraud detection efficiency, holding other factors constant. This positive association highlights AI's capacity to improve audit accuracy and reliability by automating data analysis, uncovering anomalies, and minimizing human error.Supporting the robustness of the model, the adjusted R-squared value of 0.7867 accounts for the number of predictors, confirming the explanatory power remains strong after adjusting for potential overfitting. The F-statistic of 182.0971 with an associated p-value of 0.0000 shows that the overall regression model is highly statistically significant, confirming that AI is a meaningful predictor of fraud detection in audited reports.

Additionally, the Durbin-Watson statistic of 1.79, which is close to the ideal value of 2, suggests no serious autocorrelation issues in the residuals, lending further credibility to the model's validity. The standard error of regression, 310.70, and the sum of squared residuals, 2,220,241, are acceptable considering the scale and variability inherent in financial data, indicating a good fit of the model.Moreover, the p-value of 0.0186, which is below the 0.05 significance threshold, confirms the statistical significance of AI's effect on fraud detection. Consequently, the null hypothesis which posits no significant effect of AI on audit quality is rejected. This supports the conclusion that AI significantly enhances the quality of audited financial reports. This finding aligns with existing literature. For example, Ashiru (2023) argues that AI technologies such as machine learning and data mining significantly boost auditors' capacity to detect fraud by systematically analyzing large volumes of data and identifying patterns that traditional auditing may overlook. Likewise, Ojo (2023) highlights that AI improves auditor independence and objectivity by minimizing manual biases and facilitating the early detection of fraudulent schemes embedded within financial statements. In summary, the regression findings robustly support the integration of AI into audit practice as a powerful tool to improve fraud detection and, by extension, the overall quality and reliability of audited financial statements. As AI continues to evolve, its adoption is likely to become even more critical in addressing the complexities and challenges inherent in modern financial auditing.

Conclusions

Based on the results, this study establishes that Artificial Intelligence (AI) significantly enhances audit practices, particularly in the detection and prevention of fraud. The findings indicate that machine learning, expert systems, data mining, and intelligent agents are key determinants influencing AI adoption among auditors in Nigeria. Among these, machine learning was most highly rated for its capacity to process large volumes of financial data and generate predictive insights, thereby supporting more informed audit decisions.The results further reveal a strong consensus among auditors that AI improves the reliability of audit outcomes by uncovering fraudulent activities such as deliberate omissions, misstatements, and management-level manipulation of financial records. AI-enabled tools like matching-order verification and automated anomaly detection were recognized as vital in strengthening the credibility, accuracy, and objectivity of audit procedures. Overall, the study affirms the growing relevance of AI in modern audit practice and its role in supporting transparency and accountability in financial reporting.

Recommendations

Based on the findings, the following recommendations are suggested:

- Audit firms should prioritize the implementation of machine learning tools capable of processing large datasets, identifying irregularities, and providing predictive insights to improve audit efficiency.
- Professional bodies and audit regulators should promote the adoption of expert systems that replicate auditor reasoning and reduce the likelihood of human errors, especially in complex audit situations.
- Auditors should be exposed to regular capacity-building programs that focus on AI tools such as data mining and intelligent agents, to enhance their technical skills and confidence in using these technologies.
- Regulatory institutions should establish and enforce clear guidelines that support the integration of AI in audit processes, ensuring that firms apply these tools in line with professional and ethical standards.

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