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ARTIFICIAL INTELLIGENCE AND AUDIT PRACTICES IN REGISTERED AUDIT FIRMS IN LAGOS, NIGERIA

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Abstract

This study artificial intelligence and audit practices in registered audit firms in Lagos, Nigeria was carried out to examine the effect of machine learning, natural language processing, Robotic process on audit practices in registered audit firms in Lagos state, Nigeria. The quantitative research design was employed and data was sourced from five point Likert scale questionnaire distributed to 285 respondents made up of junior, senior and audit partners in registered audit firms in Lagos out of which only 155 was returned accounting for 54%. The descriptive statistics, normality test, multi-collinearity test were all carried out. Reliability test was conducted with the aid of Cronbach Alpha and regression was used to test the hypotheses of the study. A significant outcome indicated that two out of three variables were found to have a significant and positive relationship with audit practice in registered audit firms in Lagos state Nigeria. The study concluded that there is a positive and significant relationship between artificial intelligence and audit practices. Implying that application of artificial intelligence will improve efficiency and effectiveness of audit practices and recommended that audit firms should continue to engage artificial intelligence and train their staff on more effective ways of using them in audit practices.

Keywords: artificial intelligence, audit practices, machine learning, Robotic process, Natural Language process.

Introduction

Auditing, as a bedrock of financial accountability integrity and transparency, has traditionally relied on manual processes, human expertise and judgment (jejeniwa & Mhlongo 2024). From its inception, the auditing profession has transformed to incorporate tools and frameworks that address increasing complexity and dynamism in financial systems as well as

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the financial performance and position of companies (Olojede & Erin, 2022). However, the increasing complexity and versatility of financial systems and the exponential growth in data have exposed the limitations of traditional auditing approaches.

These challenges and difficulties have catalyzed and resulted in the adoption of advanced technologies, with Artificial Intelligence (AI) emerging as a transformative and groundbreaking force in the field (Alles, 2015; Kokina & Davenport, 2017). In the 20th century, the emergence of computerized accounting systems marked the beginning of the use of technology in auditing and also paving the way for technological integration. However, the 21st century has instituted and brought about a digital revolution, with Artificial intelligence emerging as a groundbreaking and revolutionary force. In auditing, AI technologies such as machine learning, natural language processing (NLP), and robotic process automation (RPA) are revolutionizing traditional practices. These technologies automate repetitive tasks, enhance data analysis, and support decision-making processes (Kokina & Davenport, 2017)

This technological evolution presents both opportunities and challenges for auditors, affecting their roles, skills, and relevance in the auditing process. Traditionally, auditing has relied heavily on manual processes, sample testing, and human judgment. Auditors typically use these methods to evaluate financial statements, detect anomalies, and assess risk (Ganapathy, 2023). However, these traditional methods are often time-intensive and limited in scope. AI-driven auditing, on the other hand, leverages advanced algorithms to process entire datasets in real time, enhancing accuracy and efficiency. AI's capabilities, including automation, predictive analytics, and natural language processing, are transforming how audits are conducted. This technology allows for the analysis of large datasets in real-time, identifying anomalies and potential risks that may be overlooked in traditional methods. For instance, AI-driven tools like IBM Watson and Deloitte's Argus have demonstrated the potential to improve efficiency and accuracy in auditing tasks (IBM, 2020; Deloitte, 2019).

The adoption of artificial intelligence in auditing is driven by several key factors. One significant driver is the proliferation of data, (Seethamraju & Hecimovic 2022). Modern businesses generate vast amounts of information, which traditional auditing methods often struggle to process effectively. AI provides auditors with the tools to manage and analyze this complexity. Additionally, regulatory pressure plays a crucial role, as stricter compliance requirements and the growing expectation for real-time auditing have made the integration of AI increasingly essential. Finally, client demand for efficiency has been a major catalyst. Clients today expect audits that are not only faster but also more reliable, and AI-powered tools are well-equipped to meet these expectations. (Alles, 2015; Vasarhelyi *et al*., 2017)

The rapid advancement and integration of Artificial Intelligence (AI) into the auditing practice in Lagos, Nigeria have raised significant questions about its impact on the relevance of auditors and the future of the profession. AI technologies, such as machine learning, robotic process automation (RPA), and natural language processing (NLP), are revolutionizing the auditing process by automating routine tasks, analyzing vast datasets, and enhancing the accuracy of audits (Alles, 2015; Kokina & Davenport, 2017). While these innovations offer unparalleled efficiency and precision, they also challenge the traditional roles and responsibilities of auditors.

One major concern is the potential for job displacement as AI systems increasingly perform tasks historically handled by auditors, such as fraud detection, risk assessment, and financial analysis. Studies suggest that up to 40% of routine auditing tasks could be automated by 2030, raising fears about the diminishing relevance of auditors in an AI-driven environment (Frey & Osborne, 2017; World Economic Forum, 2020). This technological shift has created uncertainty about the future of human auditors in an industry that has long depended on their expertise and judgment (Brynjolfsson & McAfee, 2014).

Conversely, there is a growing argument that AI does not replace auditors but rather augments their capabilities, enabling them to focus on higher-value activities like strategic decision-making, ethical oversight, and interpreting AI-driven insights (Vasarhelyi *et al*., 2015; AICPA, 2021). However, this shift demands that auditors acquire new competencies in data analytics, programming, and technology management which are areas traditionally outside their expertise (Kokina & Davenport, 2017). Failure to adapt to these evolving demands risk making auditors less effective and less relevant in an increasingly automated world.

Moreover, the adoption of AI introduces challenges related to algorithmic biases, transparency, and accountability, all of which require careful ethical and professional oversight (Cheng *et al*., 2020). Without addressing these issues, there is a risk of compromising stakeholder trust in audit outcomes and diminishing the perceived reliability of AI-driven auditing processes. Despite these challenges, there is a lack of comprehensive research examining how the adoption of AI will reshape the auditing profession, the skills required for auditors to remain relevant, and the potential socio-economic implications of widespread AI integration (Christensen *et al*., 2021).

This study contributes significantly to the growing body of literature on artificial intelligence (AI) in auditing by offering context-specific, data-driven insights from registered audit firms in Lagos, Nigeria. While previous research has explored the implications of AI for auditing (Brown-Liburd *et al*. 2015) on audit judgment, (Issa *et al*. 2016) on automation potential, and (Munoko *et al*. 2020) on ethical concerns, few have adopted an empirical methodology in the Lagos, Nigerian context. This study distinguishes itself by examining not only the technological impact of AI tools (Machine Learning, Robotic Process Automation, and Natural Language Processing) on audit practices but also the associated risks and the evolving role of auditors in an AI-integrated environment. By surveying auditors across hierarchical roles (junior, senior, managers, and partners) within Lagos-based firms, the research provides nuanced insights into how AI adoption influences auditing efficiency, job

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responsibilities, and skill requirements. Furthermore, the study offers a robust statistical foundation for its conclusions bridging the gap between theory and practice in Nigerian auditing literature. In doing so, it adds a new layer to understanding the readiness of the Lagos, Nigerian audit profession for AI-driven transformation, and it provides practical recommendations for policy and educational reforms tailored to emerging technological demands.

This study is designed to examine the effect of machine learning, Robotic process, and Natural Language process on audit practices in registered audit firms in Lagos State, Nigeria.

Literature Review

Machine Learning (ML) in Audit practices

Machine learning is a key subset of artificial intelligence (AI), which originated with the idea that machines could be taught to learn in ways similar to how human learning. Instead relying primarily on representative sampling techniques, machine learning algorithms can provide firms with opportunities to review an entire population for anomalies. When audit teams can work on the entire data population, they can perform their tests in a more directed and intentional manner. In addition, machine learning algorithms can “learn” from auditors’ conclusions on specific items and apply the same logic to other items with similar characteristics. (Dickey, 2019)

Machine Learning (ML) represents a significant leap in the application of artificial intelligence to auditing. Unlike traditional rule-based systems, ML algorithms are designed to learn from historical data and adapt to new patterns, making them particularly effective for identifying anomalies and predicting risks. For example, in financial statement audits, ML can analyze vast datasets to detect unusual transactions, discrepancies, or trends that might indicate fraud or errors. These capabilities are especially beneficial in forensic audits, where ML models can identify subtle patterns that might be missed by traditional auditing methods (Brown-Liburd *et al*., 2015; Kokina & Davenport, 2017).

Another critical application of ML is in fraud detection. By training algorithms on historical fraud cases, ML models can identify patterns and behaviors commonly associated with fraudulent activities. This capability is particularly valuable in audits of large organizations, where manual fraud detection methods may be impractical. However, the implementation of ML in auditing is not without challenges. Auditors must develop the technical expertise to understand and validate ML models, ensuring that their predictions are accurate and unbiased. Ethical considerations, such as transparency and accountability in algorithmic decision-making, are also critical to maintaining public trust in the auditing process (Vasarhelyi *et al*., 2017; Issa *et al*., 2016). AI empowers auditors to analyze entire datasets, moving beyond the traditional reliance on sample testing. In conventional auditing, sample testing inherently carries the risk of missing material misstatements or anomalies because it examines only a fraction of the data. AI-driven data analysis eliminates this limitation by enabling full-population testing, ensuring that every transaction and entry is examined for irregularities (Kokina & Davenport, 2017).

Natural Language Processing (NLP) in Audit practices

Natural language processing (NLP) is a field of research and application that investigates how computers can be used to understand and manipulate natural language text or speech in order to perform various tasks (Schumann *et al.*, 2021). An important goal in NLP is to gain knowledge about the way people understand and use natural language. To make such knowledge usable for a computer, NLP involves different disciplines, including computer and information sciences, linguistics, mathematics, electrical engineering, electronics, artificial intelligence, robotics, and psychology (Chowdhury 2003).

Natural Language Processing (NLP) is another critical AI technology transforming the auditing profession. NLP focuses on enabling machines to understand, interpret, and generate human language. This capability is particularly valuable in auditing, where auditors often deal with vast amounts of unstructured textual data, such as contracts, financial disclosures, regulatory filings, and internal communications.

One prominent application of NLP in auditing is the extraction and analysis of contractual terms. For instance, auditors can use NLP to identify revenue recognition clauses, lease obligations, or other terms that impact financial reporting. This automated analysis significantly reduces the time required for manual document review while improving the accuracy of compliance assessments (Jurafsky & Martin, 2020, Vasarhelyi *et al.*, 2017, Alles *et al.*, 2018).

Robotic Process Automation (RPA) in Audit practices

Robotic Process Automation (RPA) is a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management (IEEE Corporate Advisory Group, 2017). In sample term RPA is software technology that designs, builds and deploys a software program, usually referred as a “robot” or “bot,” to interact with the computer application by mimicking human actions to complete specific task defined by the robot designer. RPA can automate human activities such as keyboard inputs, mouse movements, clicks, and computer screen reading. Combing these actions, a bot can perform many tasks a human can do on a computer (Shaoyu, 2022)

RPA is the simplest form of digital labor. Its significance is that it enables data to be collected, analyzed or calculated at a speed and scale far greater than a human or team of humans could manage. While the common perception of ‘robotics’ may be a robot or piece of machinery that automates a packing, picking or processing process in a factory, robotics is equally applicable to business processes, such as in the finance function, human resources,

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internal audit or external audit. RPA means that data can be processed in vast quantities, far beyond what was possible before (KPMG,2021).

Machine Learning, Robotic Process Automation and Natural Language Processing in Audit practices

Machine Learning (ML), Robotic Process Automation (RPA), and Natural Language Processing (NLP) are interconnected technologies that collectively transform audit practices by enhancing efficiency, accuracy, and insights from both structured and unstructured data. While each technology addresses a specific function, they complement each another to streamline auditing processes and enable real-time, data-driven decision-making.

RPA automates repetitive, rule-based tasks in auditing, such as gathering financial data, reconciling accounts, and generating reports. It serves as the foundational technology that prepares and organizes structured datasets for deeper analysis. For instance, RPA can extract data from multiple ERP systems and compile it into a uniform format. This organized data is then ready for advanced analysis using ML or NLP, making RPA a crucial enabler of more sophisticated technologies.

ML takes this structured data and applies predictive analytics, pattern recognition, and anomaly detection to uncover insights that may not be evident through traditional methods. In auditing, ML can process large datasets to highlight unusual patterns, such as spikes in expenses or transactions outside normal hours, which could indicate fraud. ML is particularly effective in identifying high-risk areas, allowing auditors to focus their efforts on critical tasks. RPA supports ML by ensuring clean and consistent data input, which is essential for effective machine learning analysis.

NLP, on the other hand, deals with unstructured data such as contracts, emails, and financial disclosures. This technology enables auditors to analyze textual information, extracting key insights and identifying risks or compliance issues. For example, RPA can automate the collection of contracts, while NLP scans these documents to extract relevant clauses and flag potential risks. The output from NLP can then feed into ML models to assess the likelihood of compliance violations or financial irregularities, creating a seamless flow of information.

Together, these technologies also enhance fraud detection. RPA can automate the monitoring of transactions and compile financial data, NLP analyzes communication for suspicious language or unusual phrases, and ML detects patterns or anomalies that indicate potential fraud. This combination ensures comprehensive coverage of both numerical and textual data, improving the accuracy and speed of forensic auditing.

Another key application is in real-time auditing, where RPA continuously monitors transactions, feeding data into ML models for immediate anomaly detection, while NLP provides qualitative insights by analyzing unstructured data sources. This integration enables

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auditors to identify issues promptly, ensuring compliance and reducing the risk of financial misstatements.

In conclusion, ML, RPA, and NLP are interconnected technologies that, when used together, create a powerful ecosystem for modern auditing. RPA automates data handling, ML generates advanced insights from structured data, and NLP processes unstructured data for deeper contextual understanding. This synergy reduces manual workloads, enhances audit quality, and allows auditors to focus on strategic and judgment-based roles, making these technologies indispensable in the evolving field of auditing.

Theoretical Review

The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was introduced by Fred Davis in 1986, later formalized in 1989. The model aims to explain why individuals adopt new technologies, and it identifies two key determinants of technology acceptance: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). PU refers to the degree to which a person believes a system will enhance job performance, while PEOU is the extent to which they believe using the system will be free of effort. TAM is widely used to understand the adoption of new technologies within organizations, including the auditing profession. The factors influencing the adoption of artificial intelligence (AI) tools, such as machine learning, robotic process automation (RPA), and natural language processing (NLP), are the perceived usefulness and ease of use of these technologies. Auditors, like any professional, are more likely to adopt AI tools if they believe these tools can enhance their audit effectiveness by providing better insights, improving audit accuracy, or reducing the time spent on repetitive tasks.

This study will this theory as it focuses on modalities that can make audit process simple and time serving rather than time consuming which traditional audit process does. lFurthermore, it enhances efficiency and accuracy of work performed which traditional audit lacks.

Empirical Review

Abdullah and Almaqtari, (2024) investigated the impact of artificial intelligence (AI), Industry readiness, and variables from the Technology Acceptance Model (TAM) on accounting and auditing practices in Saudi Arabia. Their study employed mediation and path analysis through Structural Equation Modeling (SEM) using SMART PLS software. Data was collected using structured questionnaires from 228 accounting and auditing professionals selected via convenience and snowball sampling. The findings revealed that AI significantly enhances efficiency, accuracy, and decision-making in auditing processes. Furthermore, the TAM framework demonstrated that the perceived usefulness and ease of use of technology mediate its readiness and adoption. Their study concluded that the integration of AI into auditing improves operational accuracy and decision-making, and emphasized the importance of strategic adoption to maximize these benefits.

Ganapathy, (2023) reviewed the applications, benefits, and challenges of AI in auditing, particularly in anomaly detection, fraud risk assessment, and improving operational efficiency. The study relied on secondary data sourced from e-journals, corporate websites, and industry-related publications. It was a theoretical review and did not involve empirical data or a defined sample size. The study highlighted that AI has transformed auditing by automating repetitive tasks and providing tools for predictive analytics, thereby improving data accuracy and fraud detection. However, challenges such as ethical concerns, data integration issues, and skill gaps among auditors were identified. The study concluded by recommending collaboration between auditors, policymakers, and researchers to ensure ethical compliance and effective AI adoption in auditing.

Ukpong *et al*., (2019) conducted a descriptive study to examine the opportunities and challenges of AI adoption in banking, accounting, and auditing within the Nigerian context. They gathered data using structured questionnaires administered to bank executives and accounting professors, supported by secondary literature. With a sample size of 45 stakeholders selected using purposive sampling, the study identified significant improvements in audit efficiency and fraud detection with AI adoption. However, it also revealed that infrastructure deficits and a lack of skilled personnel remain critical barriers to full AI integration in developing economies. The authors concluded by emphasizing the need for investments in capacity building and regulatory frameworks to address these challenges.

In another study, Ganapathy, (2023) explored the transformative potential of AI in auditing, focusing on its ability to enhance financial transparency, regulatory compliance, and fraud detection. The study was theoretical, relying on secondary sources such as academic articles, e-books, and industry reports. The findings emphasized how technologies like machine learning, NLP, and deep learning empower auditors to perform advanced data analysis and risk assessments. Despite these benefits, the study identified barriers such as data quality issues, regulatory challenges, and the growing need for technical expertise. The author concluded that addressing these challenges is critical to unlocking AI's full potential in auditing.

Vasarhelyi *et al*., (2020) conducted a study to explore the ethical implications of using AI in auditing. The objective was to provide a conceptual analysis of practical ethical and social issues arising from the adoption of AI. The research employed a conceptual analysis design using futuristic ethical frameworks, including ETICA and Anticipatory Technology Ethics. Data for the study were sourced from secondary materials such as previous studies, industry reports, and AI applications in auditing. As a conceptual study, there was no defined population or sample size, and no statistical techniques were applied. The findings revealed significant ethical risks in AI adoption, including issues like bias, lack of transparency, and responsibility gaps. The study concluded that effective policy frameworks and governance mechanisms are crucial to address these ethical challenges and ensure responsible AI use in auditing.

Popescu *et al*., (2023) analyzed the transition from digitization to AI in external public auditing, with a focus on performance management and public procurement audits. This descriptive study relied on secondary data from case studies, reports by Supreme Audit Institutions (SAIs), and industry reviews. The study's population included Supreme Audit Institutions globally, although no explicit sample size was provided. As a descriptive analysis, no statistical hypothesis testing was conducted. The findings indicated that digitization and AI adoption significantly improved the efficiency and quality of public audits. The study cited examples from SAIs in Estonia, Norway, and Korea, where AI tools were used for real-time monitoring and performance audits. The authors concluded that adopting AI in public auditing requires robust data management systems and continuous innovation in audit tools.

Iwuanyanwu *et al*., (2023) investigated the role of AI in IT audits, focusing on current practices, training requirements, and future prospects. The study employed a mixed-methods approach that combined a literature review with case study analysis. Data were sourced from secondary literature and practical case studies of organizations using AI in IT audits. The population of the study included organizations adopting AI in IT auditing; however, no explicit sample size was mentioned. The study did not apply statistical techniques, as it primarily used qualitative and case study approaches. Findings revealed that AI technologies such as machine learning, RPA, and NLP significantly enhance audit efficiency, anomaly detection, and risk assessment. However, challenges such as skill gaps, lack of interpretability, and ethical concerns remain barriers to optimal AI use. The authors concluded that continuous training, the establishment of ethical guidelines, and collaboration between IT professionals and auditors are essential for the effective implementation of AI in auditing.

Karmańska, (2022) conducted a study to explore the benefits of applying Artificial Intelligence (AI) in the audit sector, focusing on its ability to enhance efficiency, improve client communication, and automate routine tasks. Using a mixed-methods approach, data was collected via an online questionnaire targeting 206 auditing and accounting professionals and students from Poland. The findings revealed that AI adoption improves audit efficiency, enhances client service, and automates repetitive tasks, allowing auditors to focus on strategic activities. While the study highlights the substantial benefits of AI in auditing, it notes a limitation in its generalizability due to its focus on Polish respondents. The research underscores AI's transformative potential in auditing and suggests the need for further studies in diverse contexts.

Law and Shen, (2021) conducted a study to investigate the impact of Artificial Intelligence (AI) on audit quality and its role in reducing human errors. The research used a quantitative approach, employing statistical models to assess the relationship between AI adoption and audit quality. Data for the study was sourced from audit reports and quality assessments. The study focused on a population of audit firms, although the exact sample size was not specified. Regression analysis was used as the primary statistical technique to evaluate the effects of AI on audit quality. The findings concluded that AI significantly enhances audit quality by reducing human errors and providing more accurate assessments. The study emphasized AI's potential as a transformative tool for improving the precision and reliability of auditing processes.

The study by Albawwat and Frijat, (2021) explored how AI enhances communication techniques with those charged with governance and improves the detection of material misstatements in audits. The research likely employed a qualitative or mixed-methods approach, focusing on case studies or surveys. Data was collected through interviews with audit professionals or surveys targeting governance bodies. The population consisted of audit firms and governance bodies, though the sample size was not specified, it likely included a range of audit firms and governance bodies. Descriptive statistics and thematic analysis were used to identify patterns and themes in the data. The study found that AI improves communication with governance bodies and enhances the detection of material misstatements by automating routine tasks and providing more accurate risk assessments.

The study by Tiron-Tudor and Deliu, (2021) explored the benefits of AI in enhancing user experience and improving audit interfaces. The research employed a qualitative approach, focusing on interviews with audit professionals. Data was collected through interviews with audit professionals. The population consisted of audit professionals, although the sample size was not specified, it likely included a range of audit professionals. Thematic analysis was used to identify patterns and themes in the data. The study found that AI improves user experience by providing new and improved interfaces for human interaction.

The study by KPMG, (2022) aimed to examine how AI is transforming financial reporting and auditing, with a focus on its impact on risk identification and anomaly detection. The research utilized a global survey approach, gathering insights from senior executives and business leaders across 1,800 companies. Data was collected through this global survey. The population consisted of senior executives and business leaders across various industries, with a sample size of 1,800 companies globally. Descriptive statistics and trend analysis were employed to interpret the data. The study concluded that AI is significantly transforming financial reporting and auditing by enabling businesses to create smarter information flows, better identify and respond to risks, and detect anomalies more effectively.

Fedyk *et al.*, (2022) researched on the effect of AI on audit quality and labor dynamism within U.S. audit firms, using a dataset generated from about 310,000 resumes and interviews with 17 audit partners. The study discovered that AI improves audit quality by reducing material restatements and lowering the audit fees charged. However, it also led to a reduction in lower-level audit roles, showing the need for increased skills on the part of the auditors to address labor displacement.

Oluwagbade *et al*. (2024) researched on the challenges and threats as well as the opportunities of AI adoption in Nigerian accounting firms through a survey of 153 statutory auditors from 35 registered firms. AI technologies which includes machine learning and NLP were discovered to enhance and improve audit efficiency and also provide actionable insights. Despite these benefits, difficulties such as infrastructure deficits and skill gaps were identified. The authors suggested prioritizing machine learning integration as well as addressing these challenges to optimize auditing practices.

Al Nairi *et al*., (2021) explored how AI and machine learning improve professional skepticism and judgment among internal auditors in Oman. The study, based on a perception survey, found that AI enhances decision-making and efficiency. However, issues such as data validation and management attitudes were noted as barriers. The authors concluded that AI adoption improves audit quality but requires efforts to address these challenges.

Xinyu, (2024) conducted a conceptual review on AI in auditing, emphasizing its efficiency in fraud detection and anomaly identification. The study highlighted risks such as data privacy concerns and workforce change due to automation. Du concluded that while AI complements human auditors, ethical frameworks and workforce upskilling are essential to mitigate risks associated with its adoption.

Methodology

The research design adopted in this study is the quantitative research design while the population comprises of the (41) forty-one registered audit firm in Lagos state Nigeria (*Finelib.com*, 2024). The study adopted the multistage sampling technique. First, the taro Yamane known sample size formular was adopted thus $n=N/(1+N(e)^2$ to determine the sample size of 37 registered audit firms in Lagos state Nigeria. From each selected audit firm, the staff were stratified into junior auditors, senior auditors, audit managers, and partners. Respondents were then selected from each stratum to ensure that the perspectives of all key roles involved in audit practice were adequately represented. Data was collected with the aid of five point |Likert scale structured questionnaire distributed to respective respondents. Out of a total of 289 questionnaires only 155 were returned which represents 54% of the entire population. The statistical package for social science (SPSS) version 28 was to analyzed the data collected. The validity of the data was confirmed with aid of senior colleagues who confirmed the questions raised was good enough to capture the items it really measured. The reliability of the data was gauged using Cronbach Alpha as presented in the table 1 and 2

Table 1 Reliability Statistics

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Cronbach's Alpha	N of Items
.838	4

Table 2 Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
ML	14.4205	6.811	.508	.840
RPA	14.4800	5.813	.750	.774
NLP	14.3483	5.963	.700	.789
audtprac	14.3738	6.396	.645	.805

Source: Authors' computation 2025

As contained inTable 1 and 2,Cronbach's alpha for ML is 0.840, RPA is 0.774, NLP is 0.789 and audit practice is 0.805. All the above values meet the thresh hold forthe reliability test. Meaning that the interrogations raised in the questionnaire section of thisstudy correctly measured the internal consistency of the variables in our study (Pollant, 2011).

The study employed ordinary least squared regression for the test of hypotheses of the study.

The model was specified as, and in line with the hypotheses, as shown below:

AUDPRACT = F(AI) ……………………………………1

Where AI =ML, RPA, NLP ………………………………..2

$AUDPRACT=\beta_0 + \beta_1 ML_{it} + \beta_2 RPA_{it} + \beta_3 NLP_{it}$ …………………3

Where:β_0 = Constant, $\beta_1, \beta_2, \beta_3$=Model co-efficient

ML= Machine Learning, RPA= Robotic Process Automation, NLP = Natural Language Processing, AUDPRACT= Audit Practice

Data analysis

Bio-data for the respondents and their frequencies

Table 3 Bio-data for the respondents and their frequencies

Variable	Category	Frequency	Valid Percent (%)	Cumulative Percent (%)
Gender	Male	95	60.1	60.1
	Female	63	39.9	100

ISSN: 2811-1710 (Paper), ISSN: 2811-1729 (Online) Vol 6, No 1, Pgs 134 - 154: 2025

Age	18–25 years	30	19.0	19.0
	26–35 years	50	31.6	50.6
	36–45 years	57	36.1	86.7
	46 and above	21	13.3	100.0
Educational Qualification	ND	6	3.8	3.8
	BSc/HND	80	50.6	54.4
	MSc/MBA	56	35.4	89.9
	PhD	16	10.1	100.0
Position in Audit Firm	Junior Auditor	34	21.5	21.5
	Senior Auditor	60	38.0	59.5
	Audit Manager	38	24.1	83.5
	Partner	25	15.8	99.3
	Others/Invalid	1	0.6	100.0
Years of Experience	0–5 years	38	24.1	24.1
	6–10 years	34	21.5	45.6
	11–15 years	45	28.5	74.1
	16 and above	41	25.9	100.0

Source: Author's computation 2025

The table 4.1 shows the frequency of distribution of respondents by gender. Where there are 60.1% (95) males and 39.9% (63) females. This suggests that it could be generalized that there are more males that females in registered audit firms in Lagos Nigeria.

The table 4.1 shows the frequency of distribution of respondents by age. Where there are 17.5% (30) aged from 18-25 years, 29.2% (50) aged from 26-35 years, 33.3% (57) aged from 36-45 years and 12.3% (21) aged from 46 years and above. This suggests that it could be generalized that a larger percentage (33.3%) of auditors working in Lagos audit firms are aged 36-45 years.

The table 4.1 shows the frequency of distribution of respondents by educational qualification.Where there are 3.5% (6) auditors with diploma qualification, 46.8% (80) with B.Sc qualification, 32.7% (56) with M.Sc qualification and 9.4% (16) with PhD qualification.

ISSN: 2811-1710 (Paper), ISSN: 2811-1729 (Online) Vol 6, No 1, Pgs 134 - 154: 2025

This suggests that it could be generalized that a larger percentage (46.8%) of auditors working in registered audit firms in Lagos Nigeria have a BSc qualification.

The table 4.1shows the frequency of distribution of respondents by official position. Where 19.9% (34) are junior auditors, 35.1% (60) are senior auditors, 22.2% (38) are Audit managers and 14.6% (25) are partners. This suggests that it could be stated that majority (35.1%) of the respondents are senior auditors

Table 4.1 shows the frequency of distribution of respondents by years of experience in active employment. Where 22.2% (38) have 0-5years working experience, 19.9% (34) have 6-10years working experience, 26.3% (45) have 11-15 years working experience and 24% (41) have 16 years and above working experience. This suggests that it could be stated that majority (26.3%) of the respondents have 11-15 years working experience.

Table 4 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
ML	158	1.60	5.00	3.5873	.75298
RPA	158	1.20	5.00	3.5278	.80546
NLP	158	1.00	5.00	3.6595	.80777
audtprac	158	1.33	5.00	3.6340	.74356
Valid N (listwise)	158				

Source: Author's computation 2025

The mean score for Machine Learning (ML) was 3.5873 (SD = 0.75298), indicating a moderately high agreement among respondents that ML contributes positively to audit efficiency, risk detection, and fraud analysis. This suggests that ML is perceived as a beneficial tool in enhancing audit accuracy and automating complex data tasks.

Robotic Process Automation (RPA) had a mean of 3.5278 (SD = 0.80546), also reflecting a generally positive response. Respondents acknowledged the role of RPA in streamlining repetitive audit procedures, improving time efficiency, and reducing human error. The slight variability (standard deviation above 0.8) may suggest that while many auditors find RPA useful, opinions may differ based on their familiarity or the sophistication of RPA tools in their firms.

The variable Natural Language Processing (NLP) showed the highest mean score of 3.6595 (SD = 0.80777), which indicates strong agreement with its usefulness in interpreting unstructured data such as contracts, reports, and financial narratives. This is significant, as it reflects growing awareness among auditors of NLP's capacity to enhance audit insight and

ISSN: 2811-1710 (Paper), ISSN: 2811-1729 (Online) Vol 6, No 1, Pgs 134 - 154: 2025

automate textual analysis which are functions that are becoming increasingly valuable in AI-augmented auditing.

The dependent variable, Audit Practice, had a mean of 3.6340 (SD = 0.74356), suggesting that respondents generally agree that AI has improved the quality, speed, and accuracy of audit tasks in their firms. With all means above the neutral midpoint of 3.0, these results confirm that AI tools (ML, RPA, NLP) are viewed favorably by the respondents in enhancing audit effectiveness in Lagos-based firms.

Normality Tests

According to (pollant *et al.*,2002), tests of normality are used to assess the normality of the distribution of scores. A non-significant result (sig value of more than 0.05) indicates normality, and a significant result indicates non- normality. The Kolmogorov Smirnov and Shapiro Wilk Test was used for the normality test.

Table 5 Kolmogorov Smirnov and Shapiro Wilk Test of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
audtprac	.207	158	.000	.904	158	.000

a. Lilliefors Significance Correction

Source: Author’s computation 2025

The tables “sig.” column lists the p-values for both tests, which are both equal to 0.000.

The p-values being less than 0.05 indicates that there is strong evidence to reject the null hypothesis

In conclusion, we would reject the null hypothesis of normality for both the Kolmogorov-Smirnov and Shapiro- Wilk tests based on the Lilliefors Significance Correction.

Figure1 Histogram showing normality

Source: Author’s computation 2025

The histogram’s depiction of the data is fairly precise, making the data appropriate for investigation. The shape of the histogram is somewhat skewed towards the right side of the graph, suggesting that the data is appropriate for the study and the histogram is bell-shaped indicating that the data is normally distributed

Multi-collinearity test

The tolerance and variance inflation factor test were employed for the multicollinearity test as contained in table 6

ISSN: 2811-1710 (Paper), ISSN: 2811-1729 (Online) Vol 6, No 1, Pgs 134 - 154: 2025

Table 6 Multi-Collinearity Test

Model		Collinearity Statistics Tolerance	VIF
1	ML	.727	1.376
	RPA	.494	2.025
	NLP	.528	1.894

a. Dependent Variable: AUDTPRAC

Source: Author's computation 2025

These statistics suggests that there is no severe multicollinearity problem in the model. All the tolerance values are above 0.1, indicating that each independent variable provides unique information to the model. Additionally, the VIF values are close to 1, indicating a relatively low level of multicollinearity. Therefore, we can summarize the independent variables, ML, RPA, and NLP, have acceptable levels of collinearity in relation to each

other in the model.

Table 7. Model Summaryb

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.669[a]	.447	.436	.55833	1.575

a. Predictors: (Constant), NATURAL, MACLEARNIN, ROBTICPRO

b. Dependent Variable: AUDTPRAC

Source: Author's computation 2025

The R value of 0.669 indicates a moderate to strong positive relationship between the predictors and the dependent variable. R square of 44.7% of the variancein the dependent variable (AUDTPRAC) is explained by the model (i.e., the three predictors). Adjusted R square of (R^2) value of 0.436 suggests that 43.6% of the variance in AUDTPRAC is explained, after accounting for the number of predictors**.** It is slightly lower than R^2, as expected. The Durbin Watson statistic value of 1.575 is approximately 2 and this indicates absence of autocorrelation.

Table 8. ANOVA[a]

ISSN: 2811-1710 (Paper), ISSN: 2811-1729 (Online) Vol 6, No 1, Pgs 134 - 154: 2025

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38.796	3	12.932	41.484	.000[b]
	Residual	48.007	154	.312		
	Total	86.803	157			

A. dependent variable: AUDTPRAC

b. Predictors: (Constant), NLP, ML, RPA

Source: Author's computation 2025

The analysis of variance (ANOVA) results in Table 4.5 shows that the regression model has an F-value of 41.484 and the corresponding p-value of 0.000. This suggests that theoverall regression model, which includes the independent variables as predictors, is statistically significant in explaining the dependent variable.

Since the p-value is less than 0.05, the result is statistically significant. This means that the regression model as a whole is valid and that the independent variables collectively have a significant impact on audit practice in the audit firms surveyed.

Table 9. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.181	.252		4.688	.000
	maclearnin	.027	.069	.027	.384	.702
	robticpro	.432	.074	.468	5.821	.000
	natural	.227	.074	.247	3.076	.002

a. Dependent Variable: audtprac

Source: Authors' computation, 2025

As contained in Table 9, machine learning (maclearnin) has a co-efficient of 0.27, t-statistic of 0.384 and probability value of 0.702. This indicate that there is a positive but insignificant association between audit practice and machine learning. The implication could be that greater number of the audit forms in this study has not employed machine learning in their audit process.

Robotic process (robticpro) has a co-efficient value of 0.432 which implies that it has a positive relationship with audit practice in this study. This is confirmed a t-statistic value of 5.821 with probability value of 0.000, which confirms that the relationship is significant.

Natural Language processing (NATURAL) is indicated to have a co-efficient of 0.227 which is positive. It is further proved to have a t-statistic value of 3.076 and probability value of 0.002 which confirms that it is significant. Implying that audit firms in this study embrace natural language process in their audit process.

Conclusion and Recommendations

Auditing entails verification of financial records of an organization as prepared by its management and express opinion on such financial record. The opinion of the auditor is so important that a lot of people rely on it for their informed decisions. But modern business transactions has changed so is audit practice owing to advancement in technology and business dealings. It is this premises that auditors need to brace up by engaging artificial intelligence in their audit process. Based on the outcome of the test of hypotheses, we found that artificial intelligence has significant effect on audit process as two out of three variables were found to have positive and significant effect on audit process. Therefore, the study concluded that there is a positive and significant effect between artificial intelligence and audit process in audit firms in Lagos, Nigeria. The study recommend that audit firms should continue to engage artificial intelligence intheir practices and continue training should be organized by theses firms to train their staff on the use of artificial intelligence in audit practices and it enhances efficiency and effectiveness.

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