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Application of Artificial Intelligence in Audit Practices in Nigeria

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Abstract

This study empirically investigated the application of artificial intelligence (AI) in audit practices in Nigeria. In order to determine the relationship between AI and audit practices, AI (independent variable) was proxy using neural network (NN) and expert system (ES) while audit practices was the dependent variable. Two hypotheses were formulated to guide the investigation and the statistical test of parameter estimates was conducted using least squares regression model operated with E-Views.12. Survey design was adopted and data for the study was obtained through e-questionnaire survey sent to the various Staff WhatsApp Group Platform of the selected audit firms in Anambra State Nigeria. The results of the study showed that neural network and expert system have positive and significant effect on audit practices in Nigeria at 1% level of significance. Based on this, the study concludes that the use of AI in auditing enables effective audit practices in Nigeria. The study therefore suggests the need for the application of AI in audit practices as the results of the study showed its significant influence and relevance on audit practices in Nigeria.

Keyword: Artificial Intelligence; Neural Network; Expert System

Introduction

The global accounting and auditing profession is undergoing a significant transformation driven by Artificial Intelligence (AI). AI technologies are revolutionizing financial reporting, auditing procedures, and decision-making processes by enhancing efficiency, improving accuracy, and strengthening capabilities in fraud detection (Okolo et al., 2024). Internationally, the integration of AI into auditing represents a paradigm shift from traditional manual sampling methods to advanced techniques involving data analytics, machine learning, and robotic process automation (Adeyemi & Ilogho, 2024). These technologies enable the continuous auditing of entire datasets, thereby increasing coverage and providing deeper analytical insights (Efobi et al., 2024). This evolution is not merely a technological upgrade but a fundamental change in the audit approach, promising to redefine audit quality and reliability.

The potential of AI in auditing is vast. Studies indicate that AI can reduce audit time by 30–40% and significantly enhance the accuracy of risk assessments by 50–60% (Adeyemi & Ilogho, 2024). By automating routine tasks, AI allows auditors to focus on complex judgment areas, thereby optimizing the human expertise within the audit process. This shift is crucial in an era of increasing data volume and complexity, where traditional methods are often insufficient for identifying subtle patterns indicative of error or fraud. The global movement towards AI adoption sets a new benchmark for audit practices worldwide, including those in developing economies like Nigeria, creating both an imperative and an opportunity for the Nigerian auditing sector to evolve.

In the specific context of Nigeria, the adoption of AI in auditing is not just a matter of keeping pace with global trends but also a potential tool for addressing longstanding systemic challenges. The Nigerian banking sector, for instance, has been exploring AI-driven audit systems to combat fund embezzlement (Efobi et al., 2024). AI strengthens audit effectiveness by improving anomaly detection and reinforcing internal controls, thereby narrowing the opportunities for financial fraud. However, the persistent challenges of pressures and rationalizations that drive fraudulent behavior indicate that technology alone is not a panacea; it requires integration with robust ethical and regulatory frameworks.

Despite its potential, the implementation of AI within internal audit functions remains complex in developing economies. In Nigeria, the adoption of AI-driven accounting tools is slow due to significant barriers (Okolo et al., 2024). The socio-economic environment presents unique hurdles, including technical limitations, infrastructural deficits, and organizational resistance (Adeyemi & Ilogho, 2024). Furthermore, the regulatory landscape is still adapting. While there is no single, overarching AI law in Nigeria, the operational environment is increasingly shaped by the Nigeria Data Protection Act (NDPA) and guidelines from bodies like the National Information Technology Development Agency (NITDA), which emphasize data privacy, transparency, and the necessity of human oversight in automated systems (NITDA, 2021). This evolving regulatory framework adds another layer of complexity for audit firms seeking to implement AI solutions. Thus, it becomes imperative to examine the role of artificial intelligence in audit practices in Nigeria.

To achieve this purpose, we formulated the following hypotheses:

H_{01}: The use of neural network has no significant effect on auditing practices in Nigeria

H_{02}: The use of expert system has no significant effect on auditing practices in Nigeria.

2. Review of Related Literature

2.1. Artificial Intelligence

Artificial intelligence (AI) can be defined from several complementary perspectives that highlight its different facets. From a foundational, goal-oriented perspective, AI is a branch of computer science dedicated to creating machines and systems capable of performing tasks that typically require human intelligence. This encompasses a wide range of capabilities, including learning, reasoning, problem-solving, perception, and understanding language (European Commission, 2018).

Onogholo et al. (2025) describe AI as the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. This view emphasizes the functional outcome of AI systems their ability to mimic human cognitive functions.

AI refers to the capability of computer systems or algorithms to imitate intelligent human behavior. This often involves machines executing tasks and adapting their actions based on the information they collect, effectively simulating human learning and decision-making processes (Sagarika et al., 2022.). This definition captures the essence of AI as it is commonly understood in both public discourse and industry applications today.

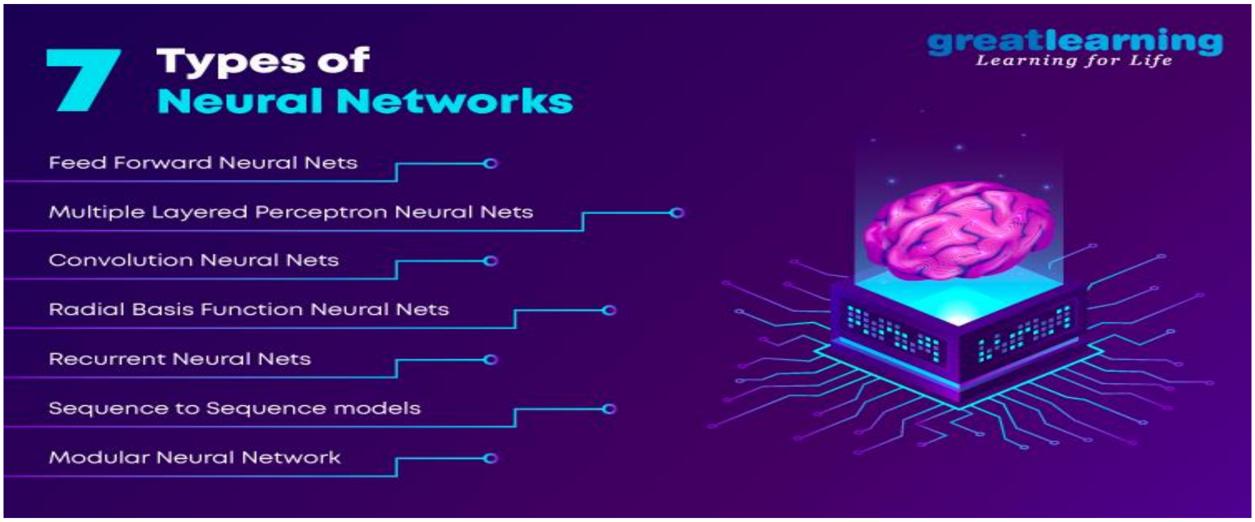
2.1.1 Neural Network

A neural network is defined as a sophisticated computational tool that enables a business risk-based auditing model. It functions by helping auditors identify the complex factors that could prevent an organization from achieving its objectives. Because they are classifiers by nature, neural networks offer the capacity to simultaneously consider multiple types of evidence, which assists auditors in assessing risk and making critical judgments, such as signaling potential management fraud (Ramamoorti et al., 2019).

According to Coakley and Brown (2020), a neural network in auditing acts as a powerful non-linear optimization and pattern recognition tool. Its primary role is to direct auditor attention to the aspects of data that are most informative of high-risk audit areas. In information-rich environments, risk assessment involves recognizing complex patterns, anomalies, and discrepancies in the data that may conceal errors or hazards. By automating this pattern detection, neural networks significantly enhance the efficiency and effectiveness of the audit process.

From a modern practice, a neural network is often categorized as a specific type of machine learning, known as an Artificial Neural Network (ANN), that has demonstrated superior performance in critical audit tasks like fraud detection. Research confirms that these methods have outperformed conventional audit practices in identifying financial statement fraud, thereby improving the overall transparency and precision of financial audits (Wei, 2025). This positions neural networks not just as analytical tools, but as transformative technologies for assuring financial integrity. This is shown on figure 1 below as thus;

Figure 1: Pictorial Representation of Neural Network



The figure 1 above shows the pictorial representation of neural network used for image recognition, predictive modeling, decision-making, and natural language processing (NLP) in audit practices.

2.1.1.1. How Neural Networks are Used in Auditing

i. **Risk assessment:** Neural networks can process various inputs (like financial data, transaction times, and account combinations) to predict and prioritize audit risks, such as the risk of material misstatement or fraud.

ii. **Anomaly detection:** They excel at identifying unusual patterns that deviate from normal behavior, such as transactions below approval thresholds, unusual timing, or unexpected account pairings.

iii. **Pattern recognition:** Neural network can find non-obvious connections between different accounts, employees, vendors, or transaction sequences that could suggest collusion or systemic issues.

iv. **Process automation:** They can be used to automate specific tasks, like distinguishing between types of leases or assessing credit risk, to help streamline the audit process.

2.1.1.2 The Process of a Neural Network in Auditing

1. **Data input:** Historical financial data and other relevant information are fed into the network.

2. **Learning/Training:** The network is trained on this data, learning the relationships between inputs and outcomes (like normal transaction patterns).

3. **Weight adjustment:** The network continuously adjusts the "weights" on its connections to minimize the difference between its output and the actual outcome in the training data.

4. **Testing and prediction:** Once trained, the network is tested on new data. It processes the new inputs and generates an output, which is a prediction or an anomaly score.

5. **Auditor review:** The auditor then uses the network's output to focus their attention on the areas it flagged as potentially high-risk for further investigation.

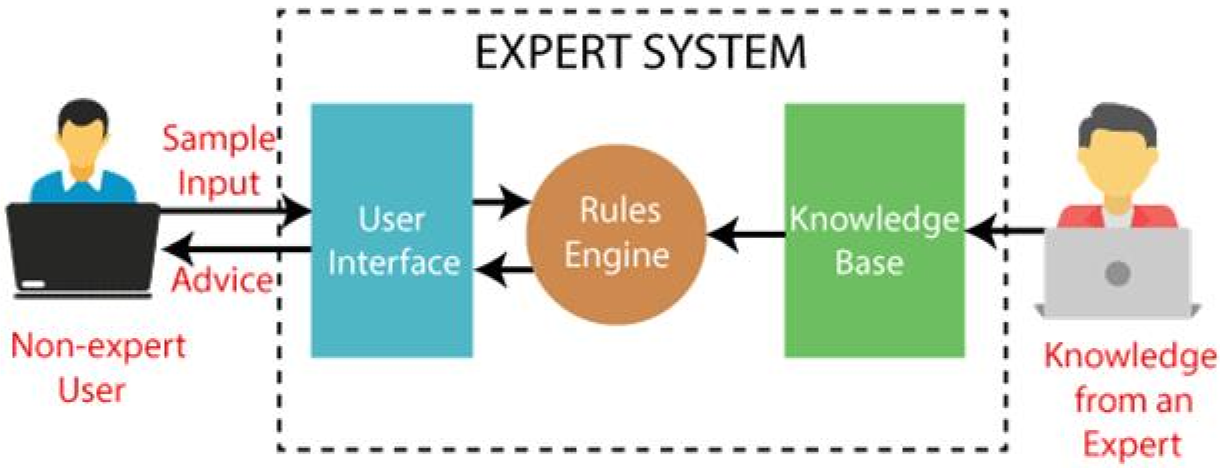
2.1.2 Expert System

An expert system in auditing can be defined from several complementary perspectives. First, from a foundational and functional standpoint, an expert system is a branch of artificial intelligence (AI) designed to emulate the decision-making abilities of a human expert. It achieves this by using a knowledge base of facts and rules, combined with an inference engine that applies logical reasoning to solve specific, complex problems within a defined domain (O'Leary, 2023). In an audit context, such a system is intended to complement, not replace, the auditor's judgment, providing structured support for tasks like internal control evaluation.

It is a sophisticated software tool that supports systems auditors in assessing risk and selecting appropriate controls to protect an organization. The system's knowledge base is built to codify the expertise and decision-making logic of seasoned audit professionals, often following a specific risk analysis methodology. This allows the system to guide less experienced auditors through complex evaluations of IT environments and security measures (Soudani, 2019).

From the lens of modern audit process enhancement, an expert system is a rule-based AI application designed to improve the efficiency and effectiveness of the audit. It can be programmed to evaluate both managerial and technical aspects of a company's information systems, helping to prioritize audit tests based on customized, company-specific rules and objectives. This application is particularly valuable in specialized areas like fraud detection and continuous auditing, where it can monitor transactions and flag anomalies in real-time (Alles & Gray, 2020). This is shown on figure 2 below as thus

Figure 2: Pictorial Representation of Expert System



The figure 2 above shows the pictorial representation of expert system used to reproduce the judgment of a human with expert knowledge in the field of auditing.

2.1.2.1 How Expert Systems Function in Auditing

a. **Knowledge Base:** This is the system's "brain," containing the accumulated knowledge of experienced auditors, including rules, facts, and relationships. This information can be gathered from experts or through automated induction from data.

b. **Inference Engine:** This is the reasoning component that uses the knowledge base to solve problems.

c. **Forward-Chaining:** Starts with known facts and applies rules to find a potential solution.

d. **Backward-Chaining:** Starts with a goal (e.g., "is there fraud?") and works backward, eliminating possibilities until a conclusion is reached.

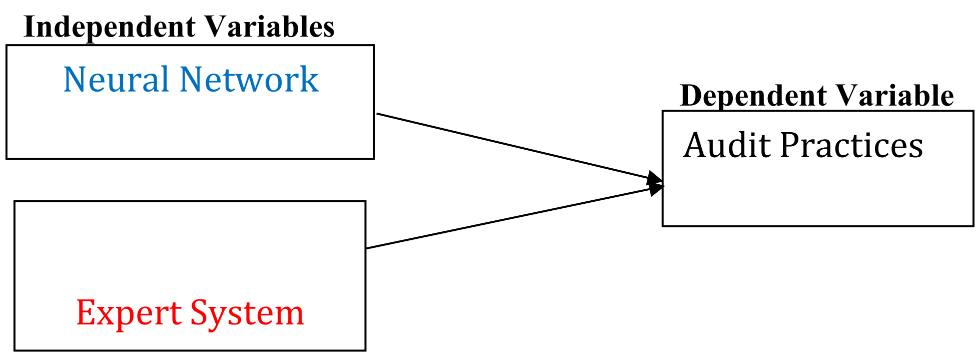
e. **User Interface:** Allows the auditor to interact with the system by inputting data and asking questions.

f. **Explanation Facility:** Explains the reasoning behind the system's conclusions, which is crucial for audit justification and learning.

2.1.2.2 The Common Applications of Expert System in Auditing

- **Audit Planning:** Helps develop a high-level audit strategy and detailed plan by analyzing risks and suggesting procedures.
- **Internal Control Evaluation:** Analyzes the effectiveness of a client's internal controls.
- **Fraud Detection:** Screens large volumes of transactions for potential fraud or errors, which can be highly cost-effective.
- **Risk Assessment:** Assists in identifying areas of high audit risk.
- **Analytical Review:** Performs complex analytical procedures to identify anomalies.
- **Estimates:** Helps auditors evaluate financial estimates made by the client, such as for bad debts or loan losses

Figure 3: The Conceptual Model for the Study



Source: Researcher's Concept (2025)

The figure 3 above shows the conceptual model of this study which focuses on an in-depth assessment of existing literature on the application of artificial intelligence in audit practices in Nigeria. Specifically, the conceptual review covers the related issues which include: scholarly definitions of concepts like neural network and expert system as it relates to audit practices in Nigeria as shown in the diagram.

2.2 Theoretical Framework

2.2.1 The Classical Theory of Artificial Intelligence (CTAI)

The Classical Theory of artificial intelligence, often termed Symbolic AI or "Good Old-Fashioned AI" (GOFAI) was propounded in the year 1956 by Claude Shannon and Arthur Samuel. It is fundamentally concerned with modeling intelligence as the mechanical manipulation of symbols through logical rules. This paradigm posits that intelligent behavior can be replicated by creating a system that represents knowledge explicitly and uses an inference engine to process that knowledge for problem-solving and deduction (Russell & Norvig, 2020). This theoretical framework has a profound and direct relationship with established audit practices, primarily because the very nature of auditing is inherently rule-based and logical.

The audit profession is built upon a foundation of structured standards, formal regulations, and systematic methodologies, such as the International Standards on Auditing (ISAs) and Generally Accepted Accounting Principles (GAAP). An auditor's task is to gather evidence and apply professional judgment within the constraints of these explicit and implicit rules to form an opinion on financial statements. This process of logical deduction and evidence-based conclusion mirrors the core tenets of Classical AI.

The most significant manifestation of this relationship is the development and application of Expert Systems in auditing. These systems are a direct operationalization of Symbolic AI theory. They function by codifying the knowledge of human audit experts into a "knowledge base" a comprehensive set of "if-then" rules derived from auditing standards, internal control frameworks, and common red flags for fraud. An inference engine then applies this rule set to specific client data to automate complex audit judgments (O'Leary, 2023). For instance, an expert system can be designed to evaluate the effectiveness of an internal control by checking a series of logical conditions, or to assess the risk of material misstatement by analyzing transactional data against a predefined set of anomalous patterns.

In essence, the Classical Theory of AI provides the conceptual blueprint for automating the structured, logical, and repetitive components of an audit. It does not seek to replace the holistic, intuitive, and ethical judgment of the auditor but rather to augment it by ensuring consistency, enhancing efficiency, and managing complexity in areas that are well-defined by rules. Therefore, the relationship is one of deep synergy: the logical formalism of Classical AI finds a natural and powerful application in the rule-governed domain of audit practice. Thus, the study was anchored on the Classical Theory of Artificial Intelligence

2.3 Empirical Review

Lawal and Adeyeye (2025) conducted a study on the effect of artificial intelligence and its associated variables on job performance. Privacy, consent, security, scalability, the role of corporations, and the changing nature of business are used as a study community and focused on Small and Medium Enterprises (SMEs) in China, business sector. To collect data from the random sample, a questionnaire was constructed. 220 managers were included in the sample. Additionally, the study took a descriptive method and analyzed the data using SPSS. The findings indicated that artificial intelligence has a statistically significant effect on employment. Performance is determined solely by factors. Additionally, the findings indicated that gender, academic credentials, and years of experience all have a statistically significant impact on work performance.

Ugo (2023) carried out an empirical investigation on the impact of artificial intelligence on accounting practice in Nigeria. The study adopted a survey research design. Data for the study were extracted from one hundred and forty-eight (148) respondents extracted from selected organizations in Abuja. A questionnaire was used as the primary instrument for data collection. The data were analyzed with the aid of frequency tables and percentages and the hypotheses were tested with probability values extracted from the regression output. The major findings of the study revealed that expert systems and neural networks contribute positively and significantly to accounting practice in Nigeria.

Onwughai (2022) evaluated the impact of the adoption of artificial intelligence and machine learning technologies on the accounting functions of business organizations. In order to collect information from respondents and examine previous academic and professional works on the topic, a survey questionnaire and qualitative literature review were used. The study demonstrated that although AI will be used to replace most programmable and monotonous accounting activities, it will also open up new opportunities for the ambitious accounting professional to advance into a more strategic and rewarding career path than just being a bookkeeper.

Akinadewo (2021) investigated the relationship between Artificial Intelligence and Accountants' Approach to Accounting Functions. The study used the research design method of a structured questionnaire. The targeted population and the sample size were 205, which comprises accountants with experience in systems application for accounting and other financial transactions functions. A purposive sampling technique was adopted to determine the respondents. The results of the analysis using OLS revealed that artificial intelligence has a significant positive impact on accountants' approach to accounting functions.

Almufadda and Almezeini (2020) reviewed the impact of AI applications on the auditing profession and found that the application of AI to audit practice is still limited to the Big

4 accounting firms. Using OLS, the suggest that the use of cloud computing and AI can lead to improvements in accounting and auditing practices.

Gentner et al. (2020) examined the role of AI in normal course of auditing. The study explored the use of regression model and confirmed that AI is utilized in auditing to identify mistakes and anomalies in financial reports quickly and to identify patterns in data and make predictions or decisions.

3. Methodology

The study adopted a survey design in order to examine the application of artificial intelligence on audit practices in Nigeria using some selected audit firms in Anambra state as a reference point. The selected audit firms in Anambra State ranges from Arthur Baubeng and Partners, Okechukwu Uchime an Co, Yans Professional Consulting & Co, Maurice S. Ndulue & Associates to Nnamdi Azikiwe University Consultancy Services (NAUCS)**.** Data for the study was collected through the use of e-questionnaire survey (Google Form) sent to the respondents through their employees WhatsApp group platform out of which 44 responses were recorded and received and were used in the data analysis. The e-questionnaire survey was designed where respondents were asked to assess the application of artificial intelligence on audit practices in Nigeria using Likert five point scales referred as: (1) To a Very High Extent (THE), (2) To a High Extent (HE), (3) Neutral (N), (4) To a Very Low Extent (TLE) and (5) To a Low Extent (LE).

Table 3.1.1: Likert five point scales

CLUSTER I: Audit Practices (Dependent Variable)

S/N	STATEMENTS	TVHE	THE	N	TLE	TVLE
1	The use of artificial intelligence has improved the efficiency of audit evidence gathering and testing procedures in my audit firm.					
2	AI tools have enhanced my ability to perform continuous auditing and real-time monitoring of financial transactions in Nigerian companies.					
3	The adoption of AI has reduced the risk of human errors and bias in audit sampling, judgment, and substantive testing.					
4	High implementation costs and lack of technical infrastructure in Nigeria limit the extent to which AI is currently used in audit engagements.					
5	The use of AI has improved audit quality by identifying unusual patterns or red flags that would otherwise be missed by traditional audit					

	procedures.					

CLUSTER II: Neural Network

S/N	STATEMENTS	TVHE	THE	N	TLE	TVLE
1	The use of neural networks has improved my ability to detect fraudulent transactions and anomalies in financial statements compared to traditional auditing methods.					
2	Neural networks have reduced the time I spend on routine substantive testing, allowing me to focus more on high-risk areas of the audit.					
3	Applying neural network models has led to more accurate audit predictions (e.g., going concern assessments or risk of material misstatement) than manual sampling techniques.					
4	Neural networks enable me to analyze full populations of transaction data rather than just samples, which has enhanced the reliability of my audit evidence.					
5	The black box nature of neural networks makes it difficult to explain or justify audit findings to clients and regulators in Nigeria.					

CLUSTER III: Experts System

S/N	STATEMENTS	TVHE	THE	N	TLE	TVLE
1	Expert systems have automated my firm's compliance testing (e.g., tax computations or payroll checks), reducing manual errors.					
2	I rely on expert system recommendations when auditing complex Nigerian tax laws or IFRS standards that require interpretation.					
3	Expert systems are integrated into my daily audit procedures, and I use them on most audit engagements.					
4	Due to insufficient training on expert systems in my organization, I do not rely on them extensively for critical audit judgments.					

5	Nigerian audit regulatory bodies (e.g., FRC) have not yet clearly accepted evidence generated solely by expert systems, which limits how extensively I use them in final audit opinions.					

The collected data was transformed to scale measurement using Likert five-point scale and the hypotheses were statistically tested using Least Squares Regression Model with the aid of E-Views 12.

3.1 Model Specification

In line with the previous studies, the present study designed a model to examine the application of artificial intelligence on auditing practices. The functional model for the study is shown below as thus:

AP = F (NN, ES)

The explicit form of regression designed for the study is shown in equation below as thus:
$AP = \beta_0 + \beta_1 NN + \beta_2 ES + \varepsilon$

AP = Audit Practice
NN = Neural Network
ES = Expert System
μ = Stochastic Term
$\beta_1 - \beta_2$ = Coefficient of Regression Equation
β_0 = Constant coefficient (intercept) of the model
'*A Priori*' is given as: $\beta_0, \beta_1, \beta_2 > 0$

Decision Rule: accept Ho if P-value >1-5% significant level otherwise reject Ho

4. Data Analysis and Results
4.1 Distribution of Respondents Responses

The distribution of the respondents responses was ex-posited on table 1 below as thus:

Table 4.1.1: Analysis of the Respondents Responses

	Item	Respondents	Percentage
	Audit Firms		
1	Arthur Baubeng and Partners	9	20
2	Okechukwu Uchime and Co	6	14
3	Yans Professional Consulting	10	23

4	Maurice S. Ndulue & Associates	7	16
5	Nnamdi Azikiwe University Consultancy Services (NAUCS)	12	27
	Total	**44**	**100.00**

Source: Field Survey (2025)

Table 4.1.1 above shows that 9 respondents representing 20% of the respondents were the staff of Arthur Baubeng and Partners; 6 respondents representing 14% of the respondents were the staff of Okechukwu Uchime and Co, 10 respondents representing 23% of the respondents were the staff of Yans Professional Consulting; 7 respondents representing 16% of the respondents were the staff of Maurice Ndulue and Associates while the remaining 12 respondents representing 27% of the respondents were the staff of Nnamdi Azikiwe University Consultancy Services (NAUCS).

4.2 Descriptive Statistics

The descriptive summary is a set of methods used to summarize and describe the main features of a datasets such as its central tendency, variability and distribution. Thus provides an overview of the data and help identify patterns and relationships between variables. This is shown on table 4.2.1 as thus:

Table 4.2.1: Descriptive Statistics

	AP	NN	ES
Mean	4.45	3.19	4.10
Median	4.25	3.11	4.02
Maximum	4.87	3.86	4.32
Minimum	4.12	3.25	3.16
Std. Dev.	0.17	0.27	0.57
Skewness	0.24	1.34	0.28
Kurtosis	2.05	3.00	2.87
Jarque-Bera	0.48	0.57	0.55
Probability	0.77	0.89	0.45
Sum	2.89	3.44	2.22
Sum Sq. Dev.	0.23	0.15	0.48
Observations	5	5	5

Source: E-View 12 Computational Results (2025)

From Table 4.2.1 above, the mean (average), maximum values, minimum values, standard deviation and Jarque-Bera Statistics (Normality Test) were shown. The results provide some insight into the determinants AI (neural network & expert system) and its effect on audit practice in Nigeria. Firstly, it can be observed that the sampled respondents were characterized by a positive audit practice (AP) value of 4.45. This implies that AP is determined by artificial intelligence in Nigeria. The distribution is platykurtic since the kurtosis (2.05) is less than 3, implying that the outliers are few. The Jarque-Bera probability of 0.77 is greater than 0.05, which means that the distribution of audit practice comes from a normal distribution.

The mean value of neural network (NN) for the sampled respondents was 3.19. This means effective audit practice is determined by the use of neural network. There is also a variation in maximum and minimum values of NN which stood at 3.86 and 3.25 respectively. This high variation in NN values among the sampled respondents justifies the need for this study that effective audit practice is determined by neural network at a degree risk of 27%. The distribution is leptokurtic since the kurtosis (3.00) is equals to 3, implying that the outliers are many. The Jarque-Bera probability of 0.89 is greater than 0.05, which means that the distribution of neural network does not deviate from normal distribution.

The average value of expert system (ES) for the sampled respondents was 4.10 with a standard deviation value of 0.57. This implies that the use of expert system enables audit practice in Nigeria at a degree risk of 57%. There is also a variation in maximum and minimum values of ES which stood at 4.32 and 3.16 respectively. This wide variation in ES values among the sampled respondents justifies the need for this study that the use of expert system is a determinant of effective audit practice in Nigeria. The distribution is platykurtic since the kurtosis (2.87) is less than 3, implying that the outliers are few. The Jarque-Bera probability of 0.45 is greater than 0.05, which means that the distribution of expert system is not different from a normal distribution.

4.3 Correlation

Table 4.3.1: Correlation Matrix

	AP	NN	ES
AP	1.0000		
NN	0.8763	1.0000	
ES	0.1625	-0.5653	1.0000

Source: E-Views 12 (2025)

Table 4.3.1 above shows the relationship between all pairs of independent variables and dependent variables used in the regression model. It reveals that all the independent variables have positive correlation with the dependent variable (AP) while some of the components of artificial intelligence has negative relationship with one another. The values on the diagonal are all 1.0000 which shows that each variable is perfectly correlated with itself.

In checking for multi-collinearity, we noticed that no two explanatory variables were perfectly correlated. This means that there is an absence of multi-collinearity in our models. Multi-collinearity between the explanatory variables may result to wrong signs or implausible magnitudes in the estimated model coefficients and the bias of the standard errors of the coefficients.

4.4: Test of Hypothesis

Table 4.4.1: Regression Result on the Application of AI in Audit Practices in Nigeria

Dependent Variable: AP
Method: Least Squares
Date: 11/01/25 Time: 3:42
Sample: 1-5
Included observations: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NN	0.797342	0.152452	5.230118	0.0045
ES	0.909874	0.082635	11.01076	0.0000
C	0.629847	0.109856	5.733387	0.0000

R-squared	0.458957	Mean dependent var	3.082637
Adjusted R-squared	0.419586	S.D. dependent var	2.985767
S.E. of regression	3.098864	Akaike info criterion	9.635635
Sum squared resid	23.34242	Schwarz criterion	7.879276
Log likelihood	7.908372	Hannan-Quinn criter.	7.246257
F-statistic	10.98874	Durbin-Watson stat	1.097467
Prob(F-statistic)	0.000000		

Source: E-View Computational Results (2025).

4.5: Discussion of Findings.

The coefficient of determination R^2 shows 0.46 indicating that the overall model explained 46 percent of the total variations in the dependent variable (audit practice). Thus shows that these variables (NN, ES) can only explain 46 percent of change in audit practice in Nigeria leaving 54 percent unexplained. This is to say that there are other factors that can contribute to effective audit practice in Nigeria other than the use of AI. The sig. (or p-value) is .0001 which is below the .01 level; hence, we conclude that the overall model is statistically significant, or that the variables have a significant and joint effect on the dependent variable. With this, the researcher affirms the validity of the regression model adopted in this study.

The results of the regression are therefore slated below as follows:

H_{01}: The use of neural network has no significant effect on auditing practices in Nigeria.

This hypothesis was tested and the result of this regression as exposited on table 4.4.1 indicates that the relationship between NN and AP is positive and significant. This is justified with the P-value (significance) of 0.0045 which is less than the 1% level of significance adopted. Likewise the result of positive coefficient of 0.797 indicates that the use of neural network is a determinant of effective audit practice in Nigeria. We consequently rejected null hypothesis and accepted the alternate hypotheses which contends that the use of neural network has significant effect on auditing practices in Nigeria. This is in tandem with the finding of Almufadda and Almezeini (2020), Onwughai (2022), Ugo (2023), who found that the use of AI ensures effective audit practices.

H_{02}: The use of expert system has no significant effect on auditing practices in Nigeria.

This hypothesis was tested and the result of this regression as exposited on table 4.4.1 indicates that the relationship between IA and AP is positive and significant. This is justified with the P-value (significance) of 0.0000 which is less than the 1% level of significance adopted. Likewise the result of positive coefficient of 0.909 indicates that the use of expert system ensures effective audit practice in Nigeria. We consequently rejected null hypothesis and accepted the alternate hypotheses which contends that the use of expert system has significant effect on auditing practices in Nigeria. This is in agreement with the priori expectations of Gentner et al. (2020), Akinadewo (2021) who found that artificial intelligence is a determinant of effect audit practices in Nigeria.

5. Conclusion

The study examined the application of artificial intelligence in audit practices in Nigeria. In addressing this, the study employed a survey research design, using e-questionnaire sent through an online platform seeking responses from the staff of the selected auditing firms in Anambra State. The results of the study revealed that audit practices in Nigeria is positively influenced by the application of artificial intelligence.

5.1 Recommendation

In lieu of the findings of the study, the following recommendations were made:

1. The study recommends that the use of neural network in auditing should be encouraged as the effectiveness of audit practices depends on it.
2. Also, the use of expert system should be encouraged as it ensures audit quality in terms of accuracy, reliability and timely financial reporting.

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