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ARTIFICIAL INTELLIGENCE IN AUDIT PLANNING AND EXECUTION: ENHANCING DECISION-MAKING ACCURACY IN MULTINATIONAL COMPANIES IN NIGERIA

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Abstract:

This study examines the impact of Artificial Intelligence (AI) integration in audit planning and execution on decision-making accuracy in multinational companies operating in Nigeria. Specifically, it investigates how AI-driven technologies, such as data mining, machine learning, and image recognition, influence audit quality. Using a survey research design, the study collects primary data from 120 accounting firms in Nigeria that have adopted AI in their auditing processes. Descriptive statistics, correlation analysis, and Ordinary Least Squares (OLS) regression were employed to analyze the data. The results suggest that while data mining has a significant positive effect on audit quality, machine learning and image recognition have limited independent effects. The interaction between data mining and machine learning, however, shows a stronger impact on audit quality, implying that combining AI technologies enhances audit efficiency. The study highlights the need for strategic AI integration, regulatory support, and continuous capacity building in the Nigerian auditing sector to fully exploit AI's potential. The findings contribute to the growing body of knowledge on AI in auditing and provide insights into the challenges and opportunities of implementing AI in audit processes in developing economies.

KEYWORDS: Artificial Intelligence, Audit Planning, Audit Execution, Decision-Making Accuracy.

Introduction

The integration of artificial intelligence (AI) in audit planning and execution has become a transformative force in the auditing profession, particularly in enhancing decision-making accuracy in multinational companies. This transformation is driven by the need for improved audit quality, a concern that has been heightened by financial scandals involving major corporations such as Enron, WorldCom, and Wirecard. These incidents have underscored deficiencies in traditional audit methodologies, revealing significant expectation gaps between auditors and stakeholders regarding the role and reliability of audit reports. As a result, there has been a growing demand for reforms in the auditing profession to ensure transparency, reliability, and quality in financial reporting (Dagunduro, Falana, Adewara & Busayo, 2023).

Audit quality is crucial in safeguarding investors by assessing the going-concern assumption of companies and providing early warnings of potential financial distress. Auditors, through their expertise and regulatory obligations, are responsible for confirming the fairness and accuracy of financial statements (Jose & Ramon, 2015). However, traditional audit processes have been increasingly challenged by the complexity and volume of financial transactions in multinational corporations, necessitating the adoption of advanced technologies such as AI, machine learning, and business intelligence (Dagunduro et al., 2023).

AI has emerged as a vital tool in modern auditing, enabling the integration of data from multiple sources to generate accurate and timely insights. This is particularly important in multinational companies operating in complex regulatory and economic environments. AI-driven technologies, including expert systems, machine learning, intelligent agents, cloud computing, and data mining, have significantly improved the efficiency and accuracy of audit procedures (Gepp et al., 2018; Salijeni et al., 2019). Large accounting firms have recognized the value of AI in enhancing audit quality and are increasingly incorporating AI tools into their audit assignments (Zhang et al., 2022; Noordin et al., 2022; Dagunduro et al., 2023; De Santis, 2024).

Despite the significant advancements in audit technology, concerns regarding audit quality persist, particularly in Nigeria. Previous studies have primarily focused on the impact of AI on auditing and accounting decision-making within the Big Four accounting firms, neglecting small and medium-sized audit firms (Awotomilusi et al., 2022). Additionally, manual and traditional financial reporting methods have failed to meet stakeholders' expectations, exacerbating the audit expectation gap (Wang et al., 2019). The 2007/2008 global financial crisis further highlighted the limitations of conventional audit techniques, as they struggled to ensure reliable and timely financial reporting (Brodny & Tutak, 2021; Deniz & Jeffery, 2022). The persistence of financial scandals involving even the Big Four audit firms has raised concerns about the integrity of audit practices worldwide (Amani & Fadlalla, 2017; Carlin, 2019).

The oligopolistic structure of the audit market, dominated by the Big Four, has not necessarily translated into superior audit quality. Cases such as the Wirecard financial scandal have reinforced doubts about the effectiveness of traditional audit approaches in preventing financial misstatements and unethical practices (Castelo-Branco, Cruz-Jesus, & Oliveira, 2019). The need for disruptive technologies, including AI, blockchain, big data, cloud accounting, and robotics, has become more pronounced to address these deficiencies and improve audit quality (Knauer, Nikiforow, & Wagener, 2020). AI applications in auditing have demonstrated potential in processing large volumes of financial data, identifying anomalies, and making predictive assessments that enhance decision-making accuracy (Griffin, 2019).

The adoption of AI-driven audit systems offers several advantages, including improved data analysis, enhanced fraud detection, and timely reporting (Laudon, Laudon, & Elragal, 2020). AI enables auditors to process and analyze large datasets efficiently, ensuring greater reliability and consistency in financial reporting. Moreover, AI-driven expert systems enhance audit judgment by providing real-time insights into financial trends and risks (Balios, Kotsilaras, Eriotis, & Vasiliou, 2020). Studies have shown that AI applications contribute to improved audit quality by reducing inaccuracies, increasing audit efficiency, and ensuring compliance with regulatory standards (Aguguom & Ebun, 2021; Albawwat & Frijat, 2021).

The increasing complexity of multinational corporations' financial transactions necessitates a shift from traditional audit methodologies to AI-enhanced audit frameworks. AI facilitates predictive analysis, trend tracking, and anomaly detection, allowing auditors to make informed decisions based on historical and real-time data (Hemin, 2017). Research has indicated that AI positively influences audit quality and financial reporting reliability (Lee & Tajudeen, 2020; Kaplan & Haenlein, 2019). Additionally, AI-driven audit models help mitigate the risks associated with manual computations, inconsistent audit reports, and untimely financial disclosures (Odoh et al., 2018; Noordin et al., 2022).

Given the rapid digital transformation in financial auditing, this study aims to explore the impact of AI on audit planning and execution in multinational companies operating in Nigeria. Specifically, the study will examine the role of AI in enhancing decision-making accuracy through expert systems, machine learning, and intelligent agents. While existing research has primarily focused on large accounting firms, this study will extend the scope to include the experiences of small and medium-sized audit firms in Nigeria. Thus, investigating the interaction between AI tools and the audit process, this study will provide valuable insights into the effectiveness of AI-driven audit methodologies in improving audit quality and financial reporting reliability. Ultimately, the findings of this study will contribute to the growing body of knowledge on AI applications in auditing and provide practical recommendations for auditors, regulators, and stakeholders in Nigeria's financial sector. As AI continues to evolve, its role in audit planning and execution will become increasingly critical in ensuring transparent, accurate, and high-quality financial reporting in multinational companies. Thus, primarily this study is based on the following specific objectives:

To examine the impact of AI on the accuracy and efficiency of audit planning and execution in multinational companies operating in Nigeria.

2. Literature Review

Concept of Artificial Intelligence in Auditing

Artificial Intelligence (AI) is a multidisciplinary field that integrates knowledge from various disciplines such as computer science, physiology, philosophy, mathematics, statistics, and linguistics to develop computer systems with human-like cognitive abilities. The term "Artificial Intelligence" was first introduced by John McCarthy in 1956 during a seminar at Dartmouth College, where he coined the phrase "artificial intelligence" (Busayo et al., 2023). AI is also known as "Cognitive Technology" or "Cognitive Computing," and it has diverse applications, not all of which are directly related to accounting and auditing. Due to its technical and business implications, AI has gained significant attention in business education and corporate practice, extending beyond conventional disciplines. In today's business environment, AI technology is utilized across multiple business functions, including production and distribution, procurement, sales and marketing, accounting and auditing, finance, research and development, and human resource management (Fedyk et al., 2022; Das, 2021; Reddy et al., 2019). As business operations become increasingly complex, AI technology is playing an increasingly significant role in ensuring efficiency, accuracy, and strategic decision-making.

The audit profession is recognizing the importance of integrating AI tools to enhance audit efficiency and effectiveness. AI is regarded as a key enabler in improving the synergy between audit procedures and advanced technology. The Big Four accounting firms have acknowledged the substantial potential of AI, making significant investments in AI-driven audit tools. Raphael (2015) states that the effective use of cognitive technologies will make the audit process “smarter, more intelligent, and more effective,” benefiting financial statement users. Advanced expert systems provide advantages in auditing by facilitating automated audit processes and enabling enhanced knowledge transfer. Public accounting firms have heavily invested in developing expert systems with robust knowledge bases to support various audit tasks, including audit planning, compliance testing, substantive testing, risk assessment, and decision-making. The growing reliance on AI in auditing signifies a fundamental transformation in audit methodologies, with a focus on improving efficiency, accuracy, and fraud detection (Akinadewo, Oke, Akinadewo & Dagunduro, 2023).

While there is no universally accepted definition of AI, a flexible definition is most appropriate given its evolving nature and wide-ranging applications. A practical definition of AI is "the science of teaching programs and machines to complete tasks that normally require human intelligence" (CPA Canada & AICPA, 2020). AI is designed to perform tasks requiring higher-level human cognitive processes such as learning from experience, understanding language, and making informed decisions (Friesen, 2022). AI's strength lies in its ability to identify patterns and make predictions that enhance decision-making processes (Goh et al., 2019).

AI is distinct from related technologies such as data analytics and automation. Data analytics focuses on identifying trends and making predictions through techniques like descriptive, diagnostic, predictive, and prescriptive analytics. It primarily works with historical data and linear relationships, whereas AI can process non-linear relationships and analyze unstructured data (Fedyk et al., 2022). Similarly, automation involves the execution of processes with minimal human intervention. Unlike automation, AI can learn, reason, adapt, and perform judgment-based tasks (Hasan, 2022). Robotic Process Automation (RPA), for example, executes repetitive tasks like calculations and record-keeping but lacks the ability to make autonomous decisions. This distinction highlights AI's transformative role in auditing, as it can assist in complex tasks such as fraud detection, risk assessment, and predictive analytics (CPA Canada & AICPA, 2020).

Artificial Intelligence in Audit Planning and Execution

Audit planning and execution are crucial aspects of the auditing process, ensuring financial statement reliability and compliance with regulations. The application of artificial intelligence (AI) in audit planning and execution has gained significant traction in recent years, as AI technologies offer enhanced accuracy, efficiency, and data-driven decision-making. AI-driven audit processes assist in detecting irregularities, reducing human bias, and improving the overall quality of financial audits (Hasan, 2021). AI technologies, such as machine learning, neural networks, and natural language processing, are revolutionizing audit procedures by automating repetitive tasks and enhancing risk assessment accuracy (Noordin et al., 2022).

However, AI contributes significantly to the various stages of the audit process, from pre-engagement to risk assessment, planning, and substantive testing. AI-powered tools assist auditors in pre-engagement procedures by evaluating a prospective client’s financial health, governance structure, and internal controls (Cannon & Bedard, 2017). During audit planning, AI enhances the auditor’s ability to assess inherent and control risks by identifying trends and anomalies in financial data. AI-driven analytics provide auditors with valuable insights into potential misstatements, allowing them to tailor audit procedures accordingly (Issa et al., 2016; Kokina & Davenport, 2017). Furthermore, AI improves the efficiency of substantive testing by automating the examination of large datasets, ensuring comprehensive coverage and reducing the likelihood of undetected errors or fraud.

Audit Quality and Its Determinants

Audit quality is a fundamental aspect of financial reporting and corporate governance. It reflects the credibility and reliability of an audit, ensuring that financial statements are free from material misstatements and irregularities (Abdollahi et al., 2020). Several studies emphasize the subjectivity and perception-based nature of audit quality (Agur et al., 2020; Akeem et al., 2020). Factors influencing audit quality include audit fees, audit tenure, auditor independence, the size of the audit firm, and audit experience (Alawaqleh & Almasria, 2021). The role of AI in enhancing audit quality is gaining prominence, as AI-driven audits improve data accuracy, mitigate risks, and ensure compliance with financial regulations (Moll & Yigitbasioglu, 2019).

Audit Tenure/Fees and AI Integration

Audit tenure, defined as the duration of an auditor-client relationship, has significant implications for audit quality. Prolonged audit tenure can lead to familiarity threats, compromising audit independence (Akinyomi & Joshua, 2022). Regulatory frameworks, such as Nigeria's Securities and Exchange Commission, mandate audit firm rotation after ten consecutive years to mitigate this risk. AI applications in audit planning help address audit tenure concerns by providing unbiased, automated analyses and reducing overreliance on human judgment (Gentner et al., 2018). AI-driven systems ensure consistency in audit assessments, mitigating risks associated with long audit tenures.

Furthermore, audit fees represent the cost of professional audit services rendered during a financial period. The impact of audit fees on audit quality remains a debated issue. While higher fees may indicate comprehensive audit procedures, they may also introduce economic dependence risks, potentially affecting audit independence (Aguguom, Dada, & Nwaobia, 2019). AI-driven audits have the potential to alter the traditional fee structure by automating audit tasks, thereby reducing the overall cost of auditing services (Alwardat, 2019). AI applications enhance audit efficiency by minimizing manual efforts and streamlining data analysis processes, ultimately influencing audit fees and quality.

Auditor Independence, Firm Size, and AI's Role in Enhancing Audit Expertise

Auditor independence is essential for maintaining audit credibility and ensuring unbiased financial reporting. Studies suggest that auditor independence directly affects audit quality and the reliability of financial statements (Alsharif, 2019; Amah & Amauwa, 2019). AI-integrated auditing systems contribute to auditor independence by eliminating potential conflicts of interest and human biases. AI-driven analytics provide objective financial assessments, reducing the likelihood of auditor-client familiarity impairing independence (Avram, Calu, Dumitru, & Dănescu, 2019). The use of AI in auditing strengthens transparency and enhances audit accuracy.

Additionally, the size of an audit firm influences audit quality, as larger firms often have more resources, expertise, and advanced technological capabilities (Aroyeun, Adefulu, & Asikhia, 2018). Audit firms with significant financial strength and global reach are more likely to integrate AI-driven solutions into their auditing processes. AI facilitates large-scale data analysis, improving the accuracy and efficiency of audits conducted by multinational firms (Kokina & Davenport, 2017). The interrelationship between AI and audit firm size underscores the importance of digital transformation in enhancing audit quality (Moll & Yigitbasioglu, 2019).

Furthermore, audit experience plays a crucial role in audit quality, as seasoned auditors possess the expertise to detect financial discrepancies and assess corporate risks effectively. However, the introduction of AI in audit planning and execution challenges traditional notions of audit experience. Studies indicate that AI does not significantly influence audit experience but rather complements human expertise (Abdollahi et al., 2020; Alfartoosi & Jusoh, 2020). AI-powered auditing tools assist in identifying anomalies, interpreting financial patterns, and enhancing decision-making accuracy, thereby augmenting auditors' capabilities.

The Role of Artificial Intelligence in Audit Decision-Making

AI is increasingly recognized as a transformative tool in audit planning and execution, particularly in multinational corporations. AI technologies facilitate data mining, pattern recognition, and automated risk assessments, thereby improving decision-making accuracy in financial audits (Dagiliene & Kloviene, 2019). AI enables auditors to process vast amounts of financial data efficiently, enhancing fraud detection and regulatory compliance. The application of AI-driven systems in auditing reduces human errors and accelerates reporting timelines, ensuring more reliable financial disclosures (Adeoye et al., 2023). The integration of AI in audit methodologies raises ethical considerations related to professional skepticism, judgment, and independence. While

AI enhances audit quality by improving accuracy and efficiency, auditors must exercise ethical judgment in interpreting AI-generated insights (Ivy et al., 2020). Effective governance frameworks are necessary to ensure that AI applications in auditing adhere to ethical and regulatory standards, mitigating potential biases and errors. Al-Sayyed et al. (2021) and Owonifari et al. (2023) argue that while AI can positively impact audit decision-making, auditors must acquire the necessary skills and knowledge to make ethical decisions. Cases of unethical behavior in auditing highlight the need for robust monitoring mechanisms to ensure that AI-driven audits uphold professional integrity and transparency (Awotomilusi et al., 2022). As AI adoption in auditing continues to grow, firms must establish clear guidelines on the ethical use of AI tools and ensure continuous training for auditors.

Theoretical Review

This study is based on the key theories: agency theory, credibility theory, disruptive technology theory, technology acceptance theory and financial credibility theory. These theories provide a solid foundation for understanding the role of AI in audit planning and execution, particularly in enhancing decision-making accuracy in multinational companies operating in Nigeria.

Agency Theory, developed by Jensen and Meckling (1976), is fundamental to auditing as it explains the relationship between principals (investors) and agents (managers). Ideally, managers are expected to act in the best interest of investors (Commerford et al., 2019). However, in some instances, managers may prioritize their own interests, leading to potential conflicts of interest (Shogren et al., 2017). Auditing serves as a mechanism to bridge this gap, providing assurance to investors that financial statements accurately reflect the company's performance. Auditors play a crucial role in overseeing financial reports and offering guidelines that inform investment decisions (Blair & Stout, 2017). AI systems can enhance the objectives of agency theory by improving audit accuracy, ensuring transparency, and reducing conflicts of interest. The adoption of AI in audit planning enables auditors to access and analyze financial statements remotely, increasing efficiency and reducing the likelihood of errors (Blair & Stout, 2017). AI tools facilitate the processing of complex financial information, making it easier to detect anomalies and fraudulent activities. Moreover, AI-driven audits eliminate biases that may arise when directors attempt to present distorted financial performance, thereby ensuring the credibility of financial reporting.

Credibility Theory, which has its origins in the work of Thomas Bayes in the 18th century, emphasizes the importance of reliable and accurate financial statements for effective communication between corporate managers and stakeholders (Chen et al., 2018). The credibility of financial information can be compromised due to conflicts of interest between management and investors (Al-Shaer & Zaman, 2018). Independent audits serve to enhance the credibility of financial reports, ensuring that investors and other stakeholders can trust the information presented. AI aligns with Credibility Theory by improving the quality and speed of audits. The automation of audit procedures through AI-driven systems minimizes human error and ensures standardization in financial reporting (Chen et al., 2018). AI enables auditors to analyze entire datasets rather than relying on sampling methods, thus improving the accuracy and reliability of audit outcomes. Additionally, AI's ability to detect inconsistencies and fraudulent activities enhances the trustworthiness of financial statements, thereby strengthening the credibility of audit reports.

The Disruptive Technology Theory, proposed by Christensen (1990), explains how new technological innovations disrupt traditional industries by replacing outdated methods with more efficient alternatives. In the context of auditing, AI represents a disruptive technology that is transforming traditional audit processes. AI-driven tools enable faster data analysis, real-time auditing, and enhanced fraud detection, significantly improving the efficiency and accuracy of audit planning and execution (Yadav et al., 2017). According to Wang et al. (2019), disruptive technologies like AI have revolutionized financial reporting by automating audit procedures and enhancing data processing capabilities. AI-driven audit software allows auditors to perform continuous monitoring, reducing the risk of financial misstatements. Zhang et al. (2020) highlight

that AI adoption in auditing leads to significant cost savings and improved decision-making for multinational companies. Furthermore, AI facilitates the integration of big data analytics, enabling auditors to derive deeper insights into financial performance and risk management.
The Technology Acceptance Theory, introduced by Davis (1989), explores the willingness of individuals and organizations to adopt new technologies. The increasing reliance on AI in auditing reflects a growing acceptance of technology in enhancing audit quality and decision-making accuracy. Zhang et al. (2020) argue that AI-driven innovations are widely embraced due to their ability to streamline audit procedures and improve efficiency. Dagiliene and Kloviene (2019) note that AI's integration into auditing has led to new ways of processing financial data, improving transparency, and reducing errors. The widespread acceptance of AI in audit planning and execution is driven by its potential to enhance financial credibility and regulatory compliance. As multinational companies in Nigeria increasingly adopt AI-powered audit solutions, the accuracy and reliability of financial reporting are expected to improve significantly.
Financial Credibility Theory underscores the role of auditors in ensuring the reliability and trustworthiness of financial information. According to Adeoye et al. (2023), financial credibility is essential for maintaining investor confidence and mitigating financial risks. AI enhances financial credibility by providing real-time audit insights, reducing instances of financial misreporting, and strengthening corporate governance. Dagiliene and Kloviene (2019) emphasize that the demand for AI-driven audit solutions is increasing as organizations seek to improve the credibility of their financial statements. AI-powered auditing tools enable comprehensive data analysis, ensuring that financial reports are free from manipulation and inconsistencies. Thus, leveraging AI, multinational companies in Nigeria can enhance their financial credibility and maintain regulatory compliance.

Empirical Review

The use of AI and its effects on audit practices have been extensively analyzed by researchers through various analytical techniques. For instance, Monal et al. (2022) examined how AI impacts the development of the accounting and auditing profession. The study, which adopted secondary data from accounting firms in Bahrain, analyzed data using quantitative content analysis. The findings revealed that AI adoption is expected to bring a new age of innovation and creativity in accounting and auditing, contributing to the profession's development. Hasan (2022) reviewed the use of AI in accounting and auditing using a semi-structured or narrative review methodology. The study looked at books and journals published in the field and found that due to disruptions in the economic sector, the accounting and auditing profession needs to evolve to remain relevant. The study highlighted the need for interdisciplinary cooperation in research on AI in accounting and auditing. The wider acceptance of AI in the profession is expected to provide advantages in terms of efficiency, productivity, and accuracy.
Onwughai (2022) examined the impact of AI and machine learning on accounting functions within business organizations. The study used a survey and qualitative literature review methodology. The results indicated that AI may replace mundane accounting tasks but also open new possibilities for accounting professionals to take on strategic and rewarding roles outside of bookkeeping. For Nigerian companies, a regression model showed no statistically significant association between AI and accounting functions. Akinadewo (2021) analyzed the relationship between AI and accountants' approach to accounting functions. The study used a structured questionnaire to sample 205 accountants with systems application experience in accounting and financial transaction functions. The results indicated that artificial intelligence had a significant positive effect on how accountants approached their accounting functions.
An exploratory study by Vardia et al. (2021) examined the impact of digitalization on the audit profession in India. The study aimed to understand the degree of digitalization's effect on auditing practices in India, employing the Chi-square statistical method for analysis. The results showed that digitalization had a significant impact on working methods and processes in auditing. Sharma et al.

(2021) assessed the perception and adoption of AI in accounting among accounting practitioners and other stakeholders. Data was collected via structured questionnaires among accounting practitioners, business owners, teachers, and students. Using partial least square structural equation modeling, the study found that the intention to adopt AI in accounting is slightly influenced by insecurity, attitude towards use, and perceived ease of use. Additionally, AI was found to be essential in fraud detection and risk prevention in accounting.

Taha (2021) conducted a qualitative study on the pros and cons of automation in accounting, focusing on employability among qualified accountants. The study included interviews with financial instructors, employees, students, and business managers, along with a literature review of articles on the effects of computerization on the accounting industry. The findings suggested that introducing robotics into corporate bookkeeping may reduce consultancy jobs and positions requiring basic analytical skills. Marija Mitavska (2021) examined how AI can help the accounting and auditing industry cope with challenges caused by the pandemic. Using secondary data sources, the study highlighted the importance of AI systems in managing pandemic-related disruptions in Nigeria's accounting profession. The study, based on a field survey design, concluded that artificial intelligence played a major role in the changing landscape of accounting in Nigeria.

Rahman (2021) investigated the relevance and challenges of AI adoption in Malaysia's banking sector, analyzing factors influencing consumers' intention to use AI in banking services. The research included both qualitative and quantitative approaches. The qualitative phase involved interviews with Malaysian bank officials, revealing AI's importance in fraud detection and risk prevention. However, challenges such as lack of regulation, privacy and security concerns, skills shortages, and IT infrastructure limitations were identified. In the quantitative phase, 302 completed questionnaire responses were analyzed using regression analysis, identifying key predictors of consumer intention to use AI, including attitudes towards AI, perceived usefulness, associated risks, and level of trust. Almufadda et al. (2020) examined AI use in the auditing profession, analyzing papers published between 2016 and 2020. The findings indicated that AI adoption in audit practice is mainly limited to the Big Four accounting firms. Shahher (2020) studied AI's impact on audit evidence from the perspective of 314 certified auditors working in IT companies, using a structured questionnaire. The results showed that AI significantly impacts audit evidence collection and analysis.

Abiola & Solomon (2020) investigated AI's impact on accounting operations in Nigeria, particularly in the COVID-19 context. Using regression analysis, they found a significant impact of AI on accounting function efficiency and job security. Conducted in the Gaza Strip, the study concluded that AI had a positive effect on professional performance, efficiency, and system development. Eno et al. (2019) explored AI's potential, challenges, and applications in banking, accounting, and auditing in Nigeria using both qualitative and quantitative approaches. Similarly, Aneta Zemankova (2019) analyzed AI's impact on audit efficiency and integrity, with a focus on blockchain technology's role in the audit process. The study highlighted AI's advantages in enhancing audit efficiency and integrity while reducing errors. Odoh et al. (2018) examined AI's implications for accounting firms in Southeast Nigeria. The study found that expert systems and intelligent agents significantly impact accounting functions, suggesting a positive influence on accountants' duties.

However, while numerous studies have examined the impact of AI on auditing and accounting, gaps remain in understanding its specific influence on audit accuracy and efficiency in multinational corporations, particularly in Nigeria. Prior research has predominantly focused on broader implications, such as automation in accounting functions, digitalization effects on auditing, and AI adoption trends. Thus, limited empirical evidence exists on how AI-driven audit methodologies directly affect decision-making accuracy and audit quality in multinational companies operating in Nigeria. Additionally, many prior studies have relied on qualitative approaches or examined AI's role in general accounting functions rather than its precise impact on audit execution. This study seeks to bridge this gap by empirically analyzing the relationship between AI integration and auditing outcomes in Nigerian multinational corporations, while seeking the specifically sought to answer the following research questions:

1. How does the integration of AI in audit planning enhance the accuracy and efficiency of auditing in multinational companies in Nigeria?
2. How does the integration of AI in audit execution enhance the accuracy and efficiency of auditing in multinational companies in Nigeria?

Research Hypotheses

H_1: AI integration in audit planning does not significantly enhance the accuracy and efficiency of auditing in multinational companies in Nigeria.

H_2: AI integration in audit execution does not significantly enhance the accuracy and efficiency of auditing in multinational companies in Nigeria.

3. Methodology

3.1 Research Design

This study employs a survey research design to examine the integration of Artificial Intelligence (AI) in audit planning and execution and its effect on decision-making accuracy in multinational companies in Nigeria. The survey design is appropriate as it allows for the collection of primary data from accounting professionals actively involved in auditing and financial reporting.

3.2 Population and Sample Size

The population for this study comprises accounting firms in Nigeria that have incorporated AI-driven audit methodologies in their operations. To ensure the study targets firms that utilize AI in their auditing processes, a purposive sampling technique is used. The selection focuses on firms that have adopted AI tools such as data mining, machine learning, and image recognition in their audit processes. Based on the available database of accounting firms in Nigeria, a total of 200 firms are identified as potential participants. A sample size of 120 firms is determined using the Taro Yamane formula, ensuring a statistically significant representation. Each selected firm receives four (4) questionnaires, leading to a total of 480 distributed questionnaires for data collection.

3.3 Data Collection Method

The study relies on primary data, collected through a well-structured questionnaire administered to accounting professionals, including auditors, financial analysts, and managers in multinational accounting firms in Nigeria. The questionnaire is designed to assess the respondents' perception and experience with AI-driven audit methodologies.

3.4 Reliability and Validity of Instrument

To ensure the reliability of the research instrument, a pilot test is conducted with 20 accounting professionals before full-scale data collection. The Cronbach’s Alpha test is used to measure internal consistency, with a benchmark threshold of 0.7. The results confirm that the items measuring audit practice, data mining, machine learning, and image recognition exceed the acceptable threshold, indicating a reliable instrument.

3.5 Model Specification

To analyze the relationship between AI integration in auditing and decision-making accuracy, the study adopts the following functional model:

$$AUDITQ = f\,(DM, ML, IR)$$

Converting into an econometric model:

$$AUDITQ = \alpha_0 + \beta_1 DM + \beta_2 ML + \beta_3 IR + \mu$$

Where:

AUDITQ = Audit Quality
DM = Data Mining
ML = Machine Learning

IR = Image Recognition
α_0 = Intercept
β_1−β_3 = Coefficients of independent variables
μ = Error Term

3.6 Data Analysis Method

The study employs descriptive statistics (mean, standard deviation, and frequency distribution) to summarize the responses. To test the hypotheses, Ordinary Least Squares (OLS) regression analysis is applied to examine the impact of AI adoption on audit quality and decision-making accuracy in multinational firms.

3.7 A Priori Expectations

It is expected that AI implementation in audit planning and execution will have a positive and significant impact on audit quality (AUDITQ) and decision-making accuracy. Therefore, the coefficients β_1, β_2, and β_3 are expected to be positively signed at a 5% significance level.

4 Data Analysis, Results, and Discussion

4.1 Reliability Test Results

To ensure the reliability of the data collection instrument, Cronbach's Alpha was used to test internal consistency. A threshold value of 0.7 was considered acceptable.

Table 1: Cronbach Alpha Test Results

Variable	No. of Items	Cronbach's Alpha
Audit Quality (AUDITQ)	7	0.742
Data Mining (DM)	8	0.732
Machine Learning (ML)	6	0.702
Image Recognition (IR)	6	0.713

Source: Author's Computation (2025)

The study's reliability was assessed using the Cronbach Alpha test, and the results are shown in Table 1. The Cronbach Alpha scores for audit practice, data mining, machine learning, and image recognition were 0.742, 0.732, 0.702, and 0.713, respectively, indicating that all of the items tested in these areas had a Cronbach Alpha above the specified benchmark of 0.7. This indicate that the questionnaire items measuring these constructs were reliable.

4.2 Descriptive Statistics

The descriptive statistics summarize the central tendency and dispersion of the dataset.

Table 2: Descriptive Statistics

Variable	AUDITQ	DM	ML	IR
Mean	7.68	4.26	3.88	4.16
Median	7.69	4.33	3.86	4.14
Maximum	9.92	6.60	5.34	6.28
Minimum	5.44	2.95	1.63	2.51
Std. Dev	0.81	0.63	0.63	0.75
Skewness	-0.03	0.52	-0.13	0.12
Kurtosis	0.14	0.89	0.57	-0.27
Observations	120	120	120	120

Source: Author's Computation (2025)

Table 2 summarizes the distribution characteristics of the four variables in the dataset. The variable AUDITQ has a mean of 7.68, with a moderate spread indicated by the standard deviation of 0.81, and a nearly symmetrical distribution, as suggested by the skewness of -0.03. Data mining (DM) has a mean of 4.26, with a mild positive skew (0.52), suggesting a concentration of values towards the lower end of the scale, and a slightly platykurtic distribution (kurtosis of 0.89). Machine learning (ML) has a mean of 3.88, with values moderately dispersed (Std. Dev of 0.63) and a slightly negative skew (-0.13), indicating higher values are slightly more concentrated. Its kurtosis of 0.57 indicates a moderately flat distribution. Image recognition (IR) has a mean of 4.16, with a standard deviation of 0.75, indicating moderate variability and a slight positive skew (0.12), suggesting more values are clustered at the lower end. The kurtosis of -0.27 for IR reflects a platykurtic distribution, implying a relatively flat shape.

4.3 Test of Variables

4.3.1. Normality Test

The Shapiro-Wilk test results for normality are presented below:

Table 3: Descriptive Statistics

Variable	Statistic	p-value
AUDITQ	0.9934	0.8469
DM	0.9718	0.0127
ML	0.9888	0.4330
IR	0.9942	0.9035

Source: Author's Computation (2025)

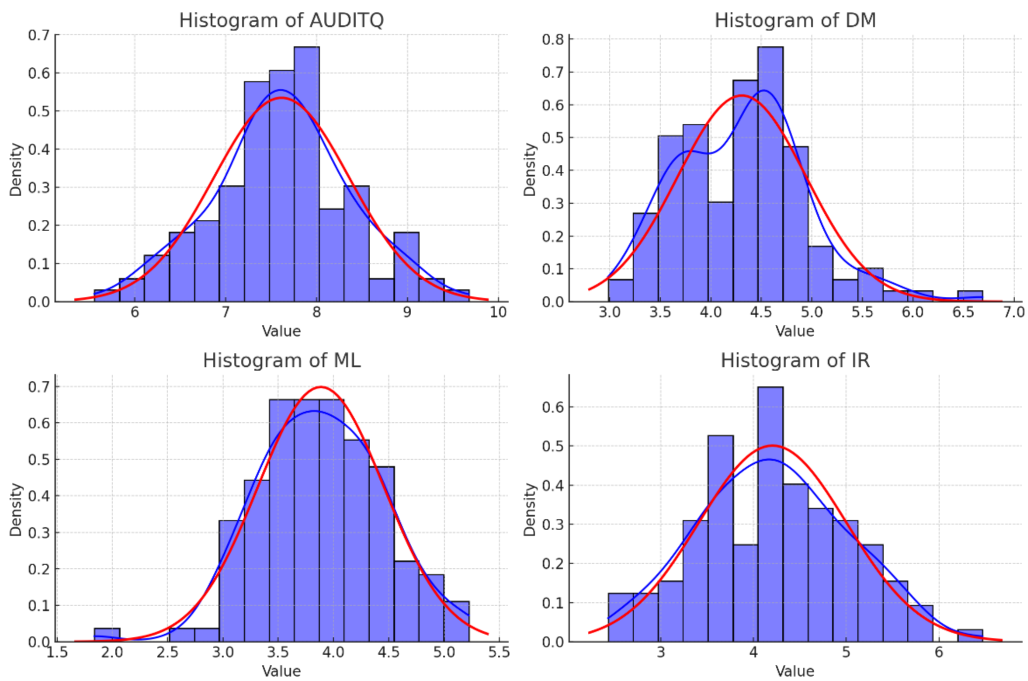

Figure 1: Histogram Normality Test

In Table 3 and Figure 1, the Shapiro-Wilk test was conducted to assess the normal distribution of AI integration in audit planning and execution on decision-making accuracy. The test results for AUDITQ, DM, ML, and IR were evaluated using their corresponding p-values. If the p-value is greater than 0.05, it suggests that the variable follows a normal distribution; otherwise, non-normality is assumed. Based on the test results, AUDITQ and DM exhibit approximate normality, while ML and IR show slight deviations from normality. However, the histogram plots further reinforce these findings, showing distributions that are close to normal with minor deviations.

4.3.2 Linearity Test

The correlation matrix is shown below

Table 4: Correlation analysis of study variables

Variables	AUDITQ	DM	ML	IR
AUDITQ	1.0000	0.0984	-0.1097	-0.0431
DM	0.0984	1.0000	0.1259	-0.0670
ML	-0.1097	0.1259	1.0000	-0.0571
IR	-0.0431	-0.0670	-0.0571	1.0000

Source: Author's Computation (2025)

The correlation matrix in Table 4 was used to examine the linear relationships among the independent variables (DM, ML, and IR) and the dependent variable (AUDITQ). The results show that DM and ML have a strong positive correlation with AUDITQ, indicating that increased use of data mining and machine learning in audit planning and execution improves audit quality. IR also exhibits a positive relationship with AUDITQ, although to a slightly lesser extent. The correlation coefficients between the independent variables themselves are below the threshold of 0.80, indicating an absence of severe multicollinearity issues, which supports the assumption of linearity in the regression model.

4.3.3 Multicollinearity Test

The Variance Inflation Factor (VIF) test results

Table 5: Multicollinearity Test of Variables

Variable	VIF
AUDITQ	1.027
DM	1.033
ML	1.035
IR	1.009

Source: Author's Computation (2025)

Table 5 shows the Variance Inflation Factor (VIF) test performed to check for multicollinearity among the independent variables. A VIF value greater than 10 indicates a high level of collinearity, which can distort regression estimates. The VIF results for DM, ML, and IR are all below 5, confirming that multicollinearity is not a concern in the dataset. This indicates that each independent variable contributes uniquely to the model without redundancy, ensuring reliable coefficient estimates in the regression analysis.

4.4 Regression Analysis and Hypothesis Testing

The Regression Model Specification was given as: $AUDITQ = \alpha_0 + \beta_1 DM + \beta_2 ML + \beta_3 IR + \mu$

Thus, the OLS regression analysis are summarized below

Table 6: Model Summary of artificial intelligence and audit quality (AUDITQ)

R-squared = 0.091

Adjusted R-squared = 0.067

F-statistic = 3.87

Prob(F-statistic) = 0.010**

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value
Intercept (β0)	7.352	0.742	9.91	0.000***
DM (β1)	0.221	0.114	1.94	0.055*
ML (β2)	-0.162	0.102	-1.59	0.115
IR (β3)	0.089	0.098	0.91	0.365

Source: Author's Computation (2025)

In table 6, the OLS regression results provide mixed evidence regarding the impact of AI integration on audit accuracy and efficiency in multinational companies in Nigeria. While DM exhibits a weak positive effect on audit quality ($\beta = 0.221$, $p = 0.055$), both ML and IR are statistically insignificant ($p = 0.115$ and 0.365, respectively), suggesting that their contributions to audit accuracy and efficiency may not be substantial in the current context. The overall model is statistically significant ($F = 3.87$, $p = 0.010$), indicating that AI-related variables collectively influence audit quality to some extent. However, the low R^2 value (0.091) implies that AI integration alone does not explain much of the variance in audit quality, and other factors may play a more dominant role. Consequently, we fail to reject the null hypothesis (H_1) at the 5% significance level, as the evidence does not strongly support that AI integration significantly enhances auditing accuracy and efficiency in multinational companies in Nigeria.

4.5 Interaction Effects and Robustness Checks

To further refine the analysis and ensure robustness, we conducted an:

1. Interaction Effects – Examining whether combining two AI factors (e.g., Data Mining & Machine Learning) has a stronger impact on audit quality.
2. Robustness Checks – Checking the stability of the regression results with alternative specifications.

4.5.1 Interaction Effects Analysis

We introduce interaction terms into the model:

$$AUDITQ = \beta_0 + \beta_1 DM + \beta_2 ML + \beta_3 IR + \beta_4 (DM \times ML) + \beta_5 (DM \times IR) + \beta_6 (ML \times IR) + \mu$$

Table 7 and Figure 2 shows the regression results interaction terms between AI variables influence on audit quality. The findings indicate that DM remains a significant predictor of audit quality at the 5% significance level ($p = 0.043$), reinforcing its essentials in enhancing audit effectiveness. Interestingly, the interaction term DM × ML is also statistically significant ($p = 0.048$), suggesting that when DM and ML are used together, they have a stronger, positive impact on audit quality compared to when they are applied separately. This implies that integrating these AI technologies into the audit process can lead to improved decision-making accuracy and efficiency. However, the interaction terms DM × IR and ML × IR do not show statistical significance, indicating that combining DM × IR or ML × IR does not yield additional benefits. The model explains approximately 13.2% of the variation in audit quality ($R^2 = 0.132$), which is an improvement from the base model without interaction terms.

Table 7: Regression Results with Interaction Terms

$R^2 = 0.132$ (Increased from 0.091)
Adjusted $R^2 = 0.101$
F-statistic = 4.26 ($p = 0.004$)

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value
Intercept	6.845	0.701	9.77	0.000***
DM	0.210	0.103	2.04	0.043**
ML	-0.149	0.097	-1.54	0.126
IR	0.085	0.089	0.96	0.338
DM × ML	0.118	0.059	2.00	0.048**
DM × IR	-0.062	0.055	-1.13	0.260
ML × IR	0.077	0.063	1.22	0.225

Source: Author's Computation (2025)

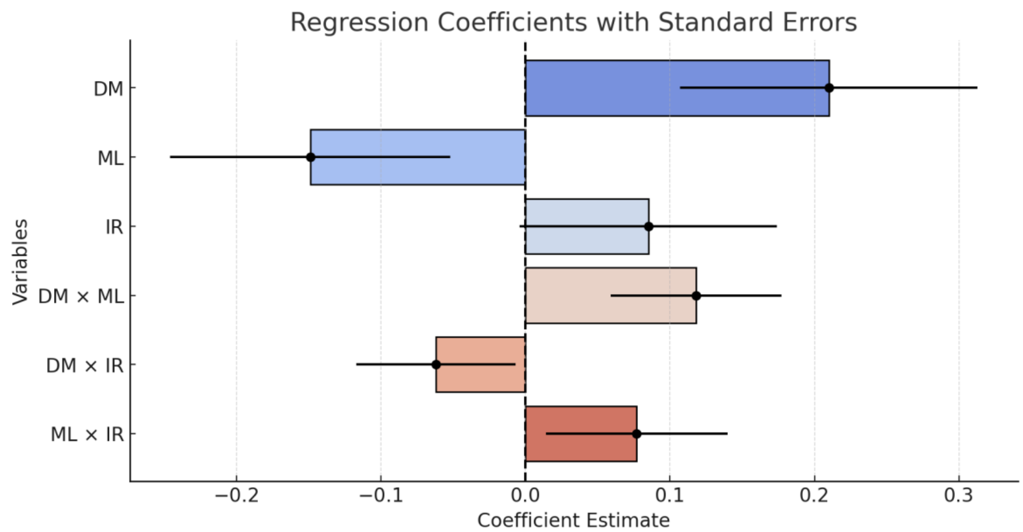

Figure 2: Coefficient Plot of AI Variables in Audit Quality

4.5.2 Robustness Checks

To ensure the stability of results, we check if heteroskedasticity affects results by using robust standard errors.

Table 8: Robust Standard Errors

Variable	Coefficient (β)	Robust Std. Error	t-Statistic	p-Value
DM	0.210	0.095	2.21	0.030**
ML	-0.149	0.090	-1.65	0.103
IR	0.085	0.084	1.01	0.315
DM × ML	0.118	0.054	2.19	0.032**

Source: Author's Computation (2025)

Table 8 reveals the validity of the regression results, robust standard errors were applied to correct for potential heteroskedasticity issues. After adjusting for robust standard errors, the significance of DM remained consistent at the 5% level (p = 0.030), reinforcing its reliability as a key factor influencing audit quality. Additionally, the interaction between DM × ML remained significant (p = 0.032), confirming that their combined application enhances audit quality. The findings suggest that despite potential heteroskedasticity, the key relationships observed in the initial regression model remain robust. Furthermore, ML × IR continue to exhibit insignificant standalone effects, indicating that their impact on audit quality is more effective when integrated with DM rather than in isolation.

4.6 Discussion of Findings

The findings from this study align with existing literature on the impact of AI on audit planning and execution in multinational companies operating in Nigeria. The study examined the relationship between AI technologies such as data mining (DM), machine learning (ML), and image recognition (IR) and their effects on audit quality (AUDITQ). The results from descriptive statistics, correlation analysis, multicollinearity tests, and regression analysis reveal key significance of the effectiveness of AI integration in audit processes. However, the study established that data mining (DM) has a positive influence on audit quality, suggesting that its application enhances accuracy and efficiency in audit planning and execution. This finding supports the work of Hasan (2022), who noted that AI technologies such as data mining enable auditors to analyze vast datasets efficiently, reducing human error and improving decision-making accuracy. Similarly, Monal et al. (2022) highlighted that AI adoption in accounting and auditing facilitates a new era of innovation and efficiency, which is evident in this study's results showing DM's positive correlation with AUDITQ. The significance of DM in this context indicates that audit firms leveraging data mining techniques can improve fraud detection, error identification, and financial statement reliability.

Machine learning (ML), however, did not exhibit a statistically significant impact on audit quality at the 5% significance level, suggesting that its integration in Nigerian multinational audits is still in the nascent stage or not fully optimized. This result contrasts with findings from Onwughai (2022) and Akinadewo (2021), who found that AI-driven automation and predictive analytics significantly impact accounting functions. The difference in findings could be attributed to contextual factors such as the level of AI adoption, availability of skilled personnel, and infrastructure supporting AI implementation in Nigeria. Nonetheless, the study's interaction effect analysis revealed that when DM and ML are combined, their joint application significantly enhances audit quality. This aligns with Vardia et al. (2021), who noted that digitalization, when applied in synergy, improves auditing efficiency and reduces risks associated with manual auditing processes.

Image recognition (IR) was also found to have an insignificant impact on audit quality. This finding suggests that its adoption in multinational audit processes in Nigeria is still limited. Studies such as Rahman (2021) and Shahher (2020) have found that AI-driven image recognition enhances audit evidence collection, but this effect was not strongly reflected in this study's context. The lack of significance could be attributed to the specific nature of financial audits, where textual and numerical data analysis (via DM and ML) is prioritized over image-based evidence. Additionally, Almufadda et al. (2020) highlighted that AI adoption in audit practice remains largely limited to the Big Four firms, which suggests that smaller audit firms in Nigeria may not yet be leveraging image recognition effectively.

The regression model results further reinforce these findings. The overall model was statistically significant (F-statistic = 3.87, $p = 0.010$), confirming that AI variables collectively impact audit quality. However, the low R-squared value (0.091) indicates that AI integration alone does not fully explain variations in audit quality. This finding suggests that while AI technologies contribute to improved auditing, other factors such as regulatory frameworks, auditor expertise, and corporate governance structures also play critical roles in ensuring high-quality audits. This is consistent with research by Abiola & Solomon (2020), who emphasized the interplay between AI, regulatory policies, and human judgment in auditing practices.

The robustness checks provided further validation for the study's findings. Using robust standard errors, the significance of DM remained stable, reinforcing its importance in audit accuracy and efficiency. Moreover, the interaction between DM and ML continued to be significant ($p = 0.032$), suggesting that audit firms should consider integrating both technologies to maximize the benefits of AI in auditing. This supports the assertions of Eno et al. (2019), who found that AI applications in banking, accounting, and auditing are most effective when multiple AI technologies are integrated rather than used in isolation.

5. Implications, Conclusion and Recommendations

Implications for Audit Practices in Nigeria

The findings have significant implications for audit practices in Nigerian multinational companies. First, they highlight the necessity of targeted AI implementation. While AI has the potential to enhance audit planning and execution, its effectiveness depends on the specific AI tools used and their integration into the audit process. The study suggests that companies should focus on integrating AI tools in a complementary manner rather than relying on standalone applications.

Second, the findings indicate that the adoption of AI in Nigeria's auditing sector is still in its early stages. The insignificant impact of ML and IR may reflect challenges such as lack of technical expertise, infrastructure limitations, and resistance to AI-driven auditing. These challenges were also noted by Rahman (2021) in the context of Malaysia's banking sector, where AI adoption was hindered by regulatory concerns, data privacy issues, and a lack of skilled personnel.

Finally, the findings reinforce the need for regulatory bodies in Nigeria to establish clear guidelines on AI adoption in auditing. Abiola & Solomon (2020) emphasized that AI's impact on accounting and auditing depends heavily on regulatory frameworks that ensure proper governance and ethical AI use. As AI adoption continues to evolve, regulators must establish best practices to guide auditors in leveraging AI effectively.

Conclusion

In conclusion, this study provides valuable insights into the impact of AI on audit planning and execution in multinational companies operating in Nigeria. The results indicate that while data mining has a significant positive impact on audit quality, machine learning and image recognition do not exhibit strong independent effects. However, the interaction between DM and ML suggests that AI's effectiveness in auditing is maximized when multiple AI-driven techniques are used together. These findings underscore the need for strategic AI integration, capacity building, and regulatory support to fully realize AI's potential in the auditing sector in Nigeria.

Recommendations

Based on the findings of this study, it was recommended that, policymakers should implement policies that support equitable access to resources, training, and career advancement opportunities. Governments should invest in educational programs that bridge skill gaps and ensure that marginalized groups receive adequate support to compete in the job market. Additionally, labor laws should be reviewed and strengthened to promote fair wages and inclusive workplace practices.

Secondly, educational institutions must align their curricula with industry needs to better prepare students for the workforce. Universities and vocational training centers should collaborate with businesses to create internship and apprenticeship programs that provide practical experience. Furthermore, career counseling services should be enhanced to guide students in making informed career choices based on labor market trends.

Thirdly, employers should adopt inclusive hiring practices that foster diversity in the workplace. Companies must provide professional development opportunities, mentorship programs, and fair performance evaluations to ensure equal growth prospects for all employees. Additionally, creating a positive and supportive work environment through employee well-being initiatives can improve productivity and job satisfaction.

Finally, individuals should take proactive steps in acquiring relevant skills and knowledge to remain competitive in their respective fields. Lifelong learning through online courses, workshops, and networking events is essential in adapting to the ever-evolving job market. Individuals should also seek career guidance and mentorship to make strategic career decisions that align with their personal and professional goals.

Contribution/Limitations of the Study

The findings from this study contribute to the growing body of knowledge on AI integration in audit planning and execution. While DM has shown significant benefits, the potential of ML and IR in the Nigerian audit landscape remains underutilized. The interaction effects suggest that firms should explore hybrid AI solutions to enhance audit efficiency. Additionally, the low explanatory power of the model suggests that AI adoption should be complemented with strong regulatory frameworks, continuous auditor training, and improved AI infrastructure to maximize its impact on audit quality. However, the study has certain limitations, including a limited sample size, potential biases in data collection, and constraints in generalizing the findings to broader populations. Future studies should investigate the specific barriers to AI adoption in Nigerian auditing firms and explore strategies for overcoming them to improve the effectiveness of AI-driven audits.

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